International Journal of Engineering Applied Sciences and Technology, 2022
Vol. 7, Issue 6, ISSN No. 2455-2143, Pages 237-242
Published Online October 2022 in IJEAST (http://www.ijeast.com)

AN OVERVIEW OF SOC ESTIMATION IN LI-ION BATTERIES WITH DIRECT MEASUREMENT METHODS AND COULOMB COUNTING

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Abstract— **The current spike in demand for new and better battery technologies and energy storage devices has intensified as a result of the recent boom in the electric car industry. A better battery management system enables a better solution for the desired application, allowing the batteries to perform to their full capacity. As a result, improving Li-ion battery technology, not only in chemistry but also in maintenance, performance, and efficiency, has become critical to meeting today's demand. Lithium-ion batteries are used in a variety of applications, and battery management systems (BMS) guarantee that the batteries last a long time and are properly utilized. BMSs are sophisticated and generate significant overhead consumption, which has an impact on the batteries. The SOC (State of Charge) Estimation, which assesses the ratio of accessible capacity to the maximum potential charge stored in the battery, is an incredibly important metric for this. The state of charge (SOC) of a battery indicates its usable capacity. It is one of the most important variables to monitor to improve the efficiency of lithium-ion batteries. Estimating the state of charge (SOC) of a battery is a serious challenge. Because the SOC is an important statistic for determining battery performance, accurate estimation of the SOC may protect the battery, reduce overcharging, extend its life, and allow the application to adopt energy-saving control measures. A battery, on the other hand, is a chemical energy storage source that cannot be accessed quickly. Estimating a battery's SOC is difficult as a result of this issue.**

*Keywords—***Open Circuit Voltage, Terminal Voltage, Impedance spectroscopy, Coulomb counting, Battery Management Systems, Li-ion batteries, Electric Vehicle, and State of Charge (SoC).**

I. INTRODUCTION

There have been numerous approaches for determining SOC, which may be divided into two categories; there are two types of measurements, direct measures and indirect measurements.
This study provides an overview of the available direct measurement methods by analyzing the methodology, benefits, and limitations, as well as comparing the existing approaches. The study gives ideal selection points for selecting a technique for analyzing the li-ion battery's SoC. Each estimating technique category has multiple distinct approaches depending on data collecting, computation methods, and so forth. i) Direct measurement methods, which include; a) Open Circuit Voltage method b) Terminal Voltage method b) Impedance spectroscopy method d) Coulomb counting method (which is also classified as a Bookkeeping Estimation Method) and ii) Indirect measurement methods, which include several new methods such as a) Adaptive artificial intelligence method which include Fuzzy based Neural Networks (ANFIS) and Artificial Neural methods, etc., b) Adaptive Filter Based Methodologies which include Kalman Filter Based Estimation methods, etc. and c) Model-Based Estimation methods which include Electrochemical methods and Electrical circuit methods.
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II. PROPOSED METHODS

A. Open Circuit Voltage Method –

The Open Circuit Voltage of the battery is referred to as OCV (battery no load condition). It is the most basic approach for estimating SOC. The OCV-SOC connection was identified by delivering a pulse load to the Li-ion battery and then allowing the battery to achieve equilibrium [9]. Furthermore, because the OCV-SOC curve is sensitive to temperature and discharge rate, the approach is only successful in calculating SOC at the commencement and end of the charging and discharging

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processes, after the battery has been withdrawn from the load for an extended amount of time.[10]

However, the connection between OCV and SOC cannot be the same for all batteries[11]. For example, The SOC of a lead-acid battery has a roughly linear relationship with its open-circuit voltage (OCV), which is given by [8].

(t) = × SOC (t) + a

where SOC(t) is the SOC of the battery at t, a is the battery terminal voltage when SOC = 0%, and a1 is obtained from knowing the value of a0 and VOC(t) at SOC = 100%. But whereas the Li-ion battery does not have a linear relationship between the OCV and SOC, instead it has a typical relationship between SOC and OCV which is shown in the below graph [13].

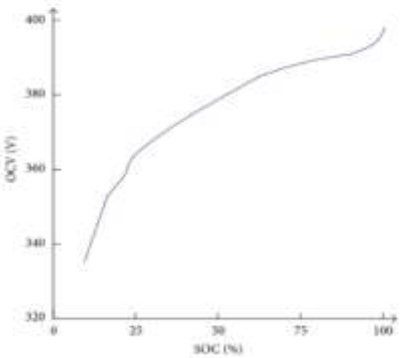

Fig. 1. SoC vs OCV

The relation between lithium-ion battery OCV and SOC is primarily functional. Fitting several test points of OCV in SOC intervals and associated models to the monotonic rising link between OCV and SOC yields the OCV-SOC curves. Thus, the most significant stage in producing an OCV curve is OCV modelling, and the quality of the OCV model directly influences the practicability and accuracy of the OCV curve. As a result, a correct OCV model for the battery must be created in order to generate a valid OCV-SOC curve. There are few models in this OCV method, some are mentioned here i) Exponential Model, ii) Polynomial Fitting Model, iii) Sum of Sin Functions Model, iv) Gaussian Model,

On the basis of such considerations, the algorithm uses a different color image multiplied by the weighting coefficients of different ways to solve the visual distortion, and by embedding the watermark, wavelet coefficients of many ways, enhance the robustness of the watermark.

B. Electro Chemical Impedance spectroscopy –

In an overview; Electrochemical Impedance spectroscopy is a method, used to measure the impedance of a system and works on the basic principle of small excitation signals. For example, AC voltage is applied to an electrochemical cell, after which the current is measured through the cell, to measure its electrochemical impedance. This process gives a response signal which is AC. Now, this response current signal can be analyzed as a sum of the sinusoidal functions, a Fourier series. Electrochemical Impedance Spectroscopy has several applications. It is a method used for studies of surfaces, batteries, photovoltaic systems, and some life science applications.

The application we are most concerned with is the SoC estimation application. Electrochemical Impedance Spectroscopy is an offline method; however, it can be made into an online method to provide an enhanced and better alternative. The high accuracy of the offline EIS technique to calculate impedance allows it to be used as a benchmark to validate other techniques.

EIS is a non-destructive and information-rich test which is conducted by galvanostatic or potentiostatic excitation signal over a wide range of frequency to obtain the impedance of the battery during charging and discharging

The excitation signals in galvanostatic and potentiostatic methods are commonly sinusoidal current and voltage and the corresponding response will be voltage and current, respectively. Based on these waveforms, the electrochemical impedance of the battery can be calculated. The impedance of the battery is obtained based on the following equations in galvanostatic mode: [14-15]

$$\Delta I = I_{max}\sin(2\pi f t),$$
$$\Delta V = V_{max}\sin(2\pi f t + \emptyset),$$
$$Z(f) = \frac{V_{max}}{I_{max}} e^{i\emptyset},$$

he extraction algorithm process is the inverse of the e where I is a sinusoidal current at frequency f, which is superimposed on the dc charging or discharging current and results in V and phase angle Ø. [14-16]

From these equations, we know that the impedance of a battery is frequency dependent and characterized by its magnitude and phase angle, according to [14]

Here, we can see the typical curve for a EIS spectrum of a lithium ion battery. mbedding process. It is assumed that the watermark as well as the see value is available at the receiver end to the authorized users.

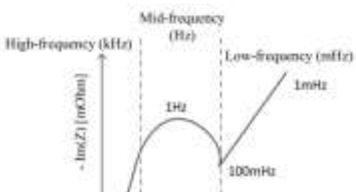

Fig. 2. EIS spectrum of a lithium ion battery

From this curve, we can see that the low-frequency tail indicates the diffusion processes inside the active material of the battery, the mid-frequency semi-circle indicates the double-layer capacitance effect, and in the high frequency region, the

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intercept of the EIS curve with the real axis is the indicator of Ohmic resistance of the battery. [14]

There have been several methods and tests done to measure SoC using EIS. There is a method for on board EIS Soc Estimation model for EV's. The measurement system is divided into two electrical isolated part, signal processing unit and battery perturbing unit, as is shown in the following figure,

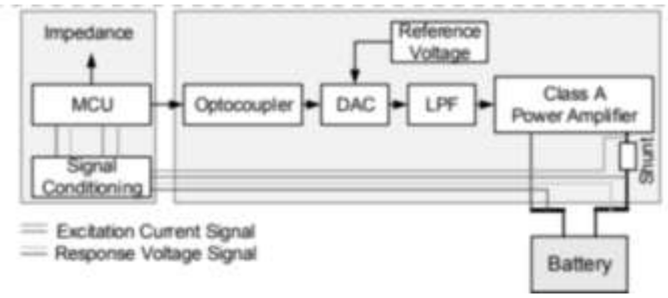

Fig. 3. On board EIS Soc Estimation model for EV's

Firstly, there is the Class A power amplifier. It is used to reduce the harmonic wave to obtain better measurements. Th DAC, produces the impulse wave with specific frequency and amplitude, which determines the excitation signal e impulse wave with specific frequency and amplitude, which determines the excitation signal. The Low Pass Filters or the LPF filter the higher harmonic of the impulse wave. The class A power amplifier acting as current source perturbs battery with sinusoidal current. The current and response voltage are sampled in MCU of signal processing unit. Then the impedance module and phase of several frequency points is calculated. It is important to note that in order to save system cost and meet the limited processing ability of MCU in vehicles, the voltage-current method is adopted to calculate impedance. [18]

Compared to the correlation method in [17], this method is low computation cost, which is important to an on-board EIS measurement system.

The equation used here is as follows:

$$|Z_x| = \frac{U_{o-max} - U_{o-min}}{G(I_{I-max} - I_{I-\min})}$$

$$\varphi_x = \frac{a-b}{c}, 0 < b < a < c = \frac{f_{sample}}{f_{signal}}$$

Here, is the impedance, is the phase of impedance, are the maximum and the minimum response voltages, G is the gain in the signal condition circuitry, are the maximum and minimum value of excitation current, a and b are the sequence number of sequence numbers of respectively. [17]

C . Terminal Voltage –

When the battery discharges, the terminal voltage reduces due to internal impedances, hence the electromotive force (EMF) of the battery is proportional to the terminal voltage. Because the EMF of the battery is roughly proportional to the SOC, the terminal voltage of the battery is likewise approximately proportional to the SOC. [20] and at diverse discharge currents and temperatures, the terminal voltage method has been used.

At various discharge currents and temperatures, the terminal voltage approach has been used. However, the predicted inaccuracy of the terminal voltage approach is considerable at the end of battery discharge because the terminal voltage of the battery abruptly drops at the end of discharge. [8]

D. Coulomb counting –

In order to determine SOC, the Coulomb counting technique analyses a battery's discharging current and integrates it over time. The Coulomb counting technique is used to calculate the SOC(t), which is calculated using the discharging current, I(t), and previously calculated SOC values, SOC(t-1). The following equation is used to determine SOC:

$$SOC(t) = SOC(t-1) + I(t).\ \Delta t / Q_n$$

And also, Coulomb counting, also known as Ampere-hour (Ah) counting, is the most often used approach for determining SOC based on the integration of charge and discharge current measurements over time. However, mistakes will accrue overtime attributable to the integration factor, which is why this method is prone to errors. Temperature, battery history, discharge current, and cycle life are all factors that influence the accuracy of the Coulomb counting approach. And also, one of the limitations of this coulomb counting technique is that cell leakage current is not taken into account. The current sensor offset might cause SOC estimates to wander. Because Li-ion batteries have a low self-discharge rate, leakage current is not an issue here, but an offset in the current sensor causes the SOC graph to drift.

The Coulomb Counting method can be enhanced by taking the Coulombic efficiency (nAh) at various temperatures and charge rates into account. It is defined as the ratio of charges removed during the discharging process to charges in during the charging process, or the ratio of discharging capacity to charging capacity.

Li-ion batteries have the highest Coulombic efficiency in the typical SOC range of all battery chemistries (exceeds 99 percent). However, estimating Coulomb efficiency is a tough process since it necessitates extremely exact equipment.

E. Event Driven Coulomb Counting –

This is a more advanced variant of the coulomb counting method. This method clearly outperforms the classic coulomb counting strategy in terms of computational efficiency, which is achieved by intelligently adding event-driven processing methodology into the suggested solution. Event-driven analogue to digital converters (EDADCs) are used in this method to efficiently capture the desired battery cell data, such as current and voltage.

. This is done in order to reduce the computational costs of the computational process post SoC estimation process. [1]
The entire process is divided into modules, and the modules worm in a flow, Firstly, we look at the Li-ion battery pack. In this method, a known technique known as Equivalent Circuit Modelling (ECM) is used, in order to have a reliable modelling of the batteries. [1,23]
As per [24], a single resistance-capacitance (RC) block is adequate to characterize all of the Li-ion cell's dynamic properties

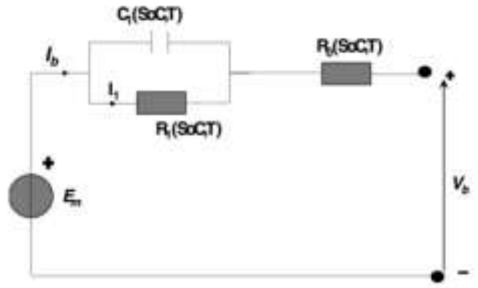

Fig. 4. Equivalent Circuit Modelling (ECM)

The ECM elements are a function of the cell SOC and temperature, which are observable during the process of estimating the ECM elements, [1,25].
By using independent experimental results, the model parameters are verified. The fitting method primarily consists of evaluating four variables, namely Em, C1, R0 and R1. The electromotive force of the principal branch is Em. In the main branch, Im is the charging/load current. [1]
The intrinsic Ohmic resistance is R0. The RC element capacitive and resistive components are C1 and R1. For simulation, the parameterized model is used. Its output, such as voltages and currents, are used for evaluating the suggested SOC estimation method.
Now that we have the model of the equivalent cell model, we can look at the arrangement of cells for the battery pack.
The battery pack is formed by arranging ten cells in series to create a 1.25kWh rated capacity. This is one cell pack. Now, 8 of these cell packs are arranged in series in order to create a battery pack of 9.92 kWh rated capacity. This creates an 80-cell battery pack.
After the battery pack is realized, we can move onto he next step in the process, the data acquisition.
The data acquisition tarts with fixed Analog to Digital converters which are integrated into the conventional BMS's. It is important to note that Nyquist sampling and rules-based processing is used in traditional BMSs [1, 26-28].
These ADC's don't work in the traditional way, hence, the general parameters such as battery voltage and current are not affective for this method, since it works only on the principle of Event Driven Sampling, which can vary their sampling rate depending on the incoming signal disparities.
As such, event-driven ADCs (EDADCs) are used in this work [28,4]. They are realized via the rules of event-driven sampling (EDS) and can vary their sampling rate depending on the incoming signal disparities. Based ont his, In the case of intermittent signals with reduced activity, tactful use of EDADCs can result in a substantial reduction in the number of samples obtained relative to traditional ADCs [28,4].

$$t_n = t_{n+1} + dt_n$$

In the case of EDADCs, a data point is only recorded once the incoming analog signal x(t) traverses one of the prefixed thresholds. Therefore, samples are irregularly distributed in time. The acquisition rate varies depending on the variations in x(t) [28].
For EDADCs, amplitudes of the samples are ideally known. However, the sampling instants are approximated by a timer circuit of step T_timer = 1/ F_timer, where F_timer is the operating frequency of this timer circuit. [1].
After careful data acquisition, keeping in mind error corrections and Sound to Noise ratios (SNR), we can move onto the event riven coulomb counting. The main advantages of over the counter analog approaches are the configurability, precession, and availability of mature computer-aided design (CAD) tools. In this sense, in contemporary BMSs, battery parameters, like voltage, temperature and current, are no longer processed in the analog domain and are instead digitized and processed later on with available state-of-the-art digital processing algorithms. [1,29]

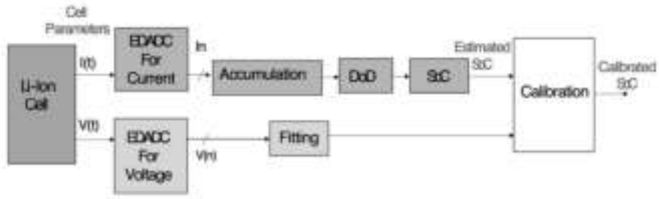

Fig. 5. Block diagram for novel idea

III. RESULT

The results for the all above mentioned method are given below in the table

Method	**Result**
Open-Circuit Voltage	This is a more efficient method several other estimation methods use data acquisition using OCV models, however, the OCV method on its own isn't a solution for cells with flat SoC-OCV curves. This, combined with the fact it is an Offline technology long rest time is required.
Terminal Voltage	the predicted inaccuracy of the terminal voltage approach is considerable at the end of battery discharge because the terminal

	voltage of the battery abruptly drops at the end of discharge. This makes the terminal end voltage method the least efficient method for SoC estimation indirect measurement methods
Electrochemical Impedance spectroscopy	The high accuracy of the offline EIS technique to calculate impedance allows it to be used as a benchmark to validate other techniques. The electrochemical impedance Spectroscopy method is viable only if it is applied in the form of a compact, efficient, and cost-effective onboard method for EV's, otherwise, The bulky and costly EIS measurement equipment can't be used in vehicles directly, even though methods based on EIS are effective. On-board EIS measurement system design can only be seen in a limited number of literatures. [13-19]
Coulomb Counting	This is one of the most efficient and methods for the SoC estimation method. Its simplicity and easy implementation allow for it to be the most favored method of direct measurement models. However, it is susceptible to errors in the initial SoC, which is resolved in post computation and error analysis. Several models allow for initial SoC determination algorithms to be more efficient to eliminate maximum error.
Enhanced Coulomb Counting (Event Driven)	This method is an enhanced version of coulomb counting. This method improves the computational effectiveness of the traditional coulomb counting approach, which is realized by intelligently incorporating the methodology of event-driven processing in the proposed solution.

Table -1 Experiment Result

IV.CONCLUSION

In this paper, we have provided a study of all the direct measurement methods, along with their advantages and drawbacks. From terminal end voltage to an enhanced model of coulomb counting, eliminating error margins and providing better data acquisition methods. In face of the constantly increasing demand for better battery packs as the demand for EV's go up, we need to provide more efficient SoC estimation methods. For example, this paper provided the method of SoC estimation known as Electrochemical Impedance Spectroscopy, and then stating the drawbacks, it being very bulky, providing an issue for including it in EV's, and then providing an On-board method of EIS, effectively tackling the issues with the method. We have also provided a better and more efficient enhanced version of Coulomb Counting. These methods will allow teams and projects to better select the most suitable method for SoC estimation of their Li-ion battery packs based on their requirements.

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