BIO Web of Conferences **97**, 00092 (2024) https://doi.org/10.1051/bioconf/20249700092
ISCKU 2024

Review on li-ion battery model used in electrical vehicle

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Abstract In recent years, battery models have become increasingly crucial, particularly with the surge in electric vehicle usage within the transportation sector. Accurate models are essential for assessing battery performance and devising effective battery management systems. Various modeling approaches exist in literature, each carrying its own set of advantages and drawbacks. Typically, more intricate models offer precise results but demand greater computational resources and entail time-consuming, costly laboratory tests for parameter determination. Hence, for first stage assessments and battery managing system designs, models employing simpler parameter documentation procedures are the most viable and suitable options. The presence of a precise battery model within a simulation platform holds immense significance in crafting efficient battery-powered systems. Absolutely! The lithium-ion battery model is a standout option owing to its potential as an energy storage system, particularly for renewable technology applications. This is largely due to its remarkable power compactness and energy storage capabilities.

1 INTRODUCTION

LATELY, the mounting concerns over environmental matters like atmospheric pollution and the dependence on fossil fuels have sparked a fresh perspective on energy—one that prioritizes green, ecological, and economical solutions. The widespread adoption of this energy concept is a crucial aim for the social and economic advancement of numerous countries. However, a prominent challenge facing this form of energy is its storage complexities. Advancements in production technologies are intricately linked to evolution in stowage technology.

The ubiquitous usage of renewable supplies, owing to their inherent variability, calls for a continuous deployment of electrical packing systems. Within this realm, lithium-ion batteries (LIBs) hold a prominent place in literature. As one of the utmost sophisticated rechargeable batteries, they have garnered considerable devotion from both investigators and businesses companies over the past few periods. The advantages of lithium-ion (Li-ion) batteries are extensive, spanning power and energy compactness, appraised lifespan, employed temperature choice, and capacity. Since the introduction of the initial rechargeable LIBs in 1976, significant technological advancements have been made within a decade. Li-ion batteries have seen a remarkable surge in usage for energy storage purposes, aiming to balance the intermittent nature of renewable energy from renewable supply on the electricity network and to stock surplus energy generated through times of excess source and lower-slung claim. Certainly, cutting down the construction costs of huge-scale LIBs for network applications is still essential**.**

Decarbonization of the transportation sector is a pivotal aspect towards achieving carbon neutrality, and this is existence addressed globally by mutually public and private entities. LIBs are the main energy supply for (EVs), shaping the pace and quality of EV development [1].

Extending the lifespan of EV battery packs is a significant challenge due to factors like overcharging, high temperatures, and over-discharging, all of which can diminish the battery pack's lifetime and usable capacity. Hence, precise State of Charge (SOC) measurements are crucial for managing battery usage [2]. The efficiency and reliability of a Battery Monitoring System (BMS) are pivotal for ensuring the safe operation of Li-ion batteries. Several studies have delved into modeling Li-ion batteries using Thévenin equivalent circuit models, aiming to accurately represent battery behavior. These models, such as third-order RC network models and improved first-order Thévenin models, have showcased high accuracy when validated against experimental data obtained from charge/discharge cycles

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Li-ion batteries, categorized as "Secondary Batteries (SB)," are highly favored because of their chargeability, energy and power ratios competed with to other battery kinds like nickel-metal and lead-acid hydride batteries. Understanding and predicting Li-ion battery behavior, including parameters such as state of charge (SOC), are crucial to designing circuits that achieve high power performance and efficiency. The SOC of the battery-operated is intricately associated to kept control charges (Q) and integrated current (I) passing over the battery. The SOC of a battery is determined by dividing its current capacity by its nominal

capacity. Precise measurement of State of Charge (SOC) is crucial for effectively managing the charging and discharging processes of batteries, especially in the context of Hybrid Electric Vehicle (HEV) applications. However, there isn't a specific sensor available to directly measure SOC. C. Park presented an algorithm reliant on physical measurements for SOC estimation, but the specifics of this method are necessary for accurate determination. This algorithm represent in formula (1) [3].

SOC = 1 – (1 – 1/Q $\int \boldsymbol{i(t)dt}$ [3] (1)

The electric transportation market demands exceptional performance and groundbreaking designs. Actually, having accurate models augment imperative. Parameters like as State of Charge (SOC), State of Health (SOH), Open Circuit Voltage (OCV), along with monitoring currents and voltages, become pivotal for designing efficient energy storage systems. This awareness is vital due to the significant impact of nonlinear physical effects within batteries on their lifespan. In literature, various modeling approaches exist, broadly categorized into three main types: electrochemical, mathematical, or electrical methods [2]. The objective of the article referenced as [4] is to conduct a comparative analysis of three distinct parameter identification techniques and modeling approaches. Specifically, It evaluates the effectiveness and suitability of the changed Thevenin model, Shepherd model and the Rint model,.

In study outlined in article [5], a Lithium polymer battery pack from a trade Electric Vehicle (EV) was utilized. This pack consisted of 96 cells connected in series, each cell having a voltage of 3.7V. The entire battery pack had a total capacity of 80Ah and exhibited a notable self-discharge rate, measuring less of 5% over the span of one month. The experimentations, as detailed in reference [6], According to their findings, this particular battery type has a self-discharge rate of less than 3% per month based on their findings. The SOC appearance delineated in this reference [7] serves as the foundation for generating models, as it correlates with various factors: current, temperature, cycle count, and Discharge of oneself. As a result of the use of this estimator, two models are created in this study with the help of this estimator, specifically designed to suit the performance of these batteries. The comparison between these models utilizes the Mean Squared Error (MSE) index, contrasting them with data provided by the Battery Management System (BMS) of the Electric Vehicle (EV).

In reference [2], a composite model comprising a second RC parallel systems equivalent circuit is employed for creating both a battery pack model and also a single battery cell model, Figure 1 depicted those models. That model combines elements from both the runtime based and Thevenin based models. The runtime based component includes a capacitor and a controlled current supply, which are working to expect the battery's SOC and runtime.

That's a great way to capture the battery's behavior during changing conditions! The Thevenin-based model with components like open circuit voltage (V_{OC}), internal resistance, and RC systems is tailor-made to replicate and understand the battery's dynamic responses.

2 THE BATTERY MODEL

The model selected as outlined in reference [8] is a first-order equivalent circuit model, illustrated in Figure 1. This model incorporates a series resistor, Rs, representing the ohmic resistance of the battery, alongside a parallel RC collection representing the separation resistance and capacitance. The Voc symbolizes the voltage open circuit of the LIB.

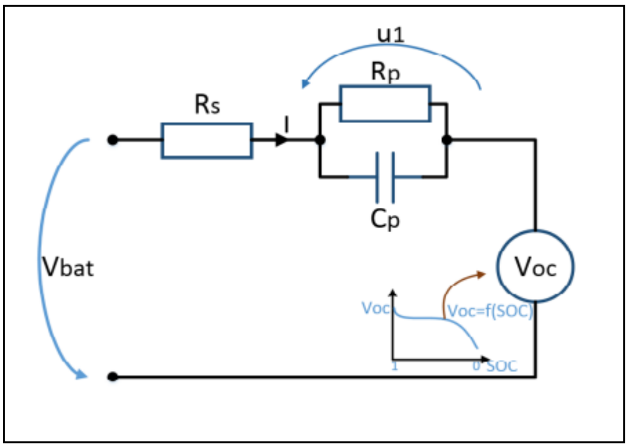

Fig. 1. Model of circuit equivalent to the first order

The typical model presented in reference [9] combines an electrical classical model with a thermal model used for the battery. This integrated framework accounts for temperature fluctuations affecting three key electrical model variables: the divergence voltage (K), battery constant voltage (E0), and the exponential coefficients A and B. If tried streamline the resulting model, they overlook the thermal belongings on coefficient A due to its close relationship with E0. However, since the B coefficient significantly influences the exponential aspect of the distinguishing curves, the authors suggest accounting for the thermal effects on B for a more comprehensive representation.

In [10], the author introduces a LIB model utilizing the Equivalent Circuit Model (ECM), incorporating a temperature function to account for temperature variations. The ECM, known for providing a simplified explanation of lithium-ion battery subtleties with less statuses and parameters, is particularly suited for real-time applications due to its low complexity. The SOC of a battery signifies the currently accessible practical energy within the current series and can be formally well-defined as per reference [22].

$$SOC(t) = SOC(t_0) - \frac{\int_{t_0}^{t} I(\tau)d\tau}{Q_c} \quad (2)$$

where I symbolize the current, t_0 symbolizes the initial time, and Q_c symbolizes the normal capacity. Coulomb counting, which involves calculating the State of Charge (SoC) by mensuration the discharging current and participating it over time, is a commonly used method. However, it's prone to issues such as extended-term point and the absence of a reliable orientation point. To maintain accuracy, regular calibration of the SoC becomes necessary. Discriminating (1) with reverence to t, we have:

$$SoC\ (t) = \frac{-I(t)}{Q_c} \quad (3)$$

The model can undergo calibration by employing the measured terminal voltage, which can be resultant from V_{OC}. The V_{oc} is linked to the physical process of lithium-ion interpolation / de-interpolation and is represented as a nonlinear objective of the SOC. Practically, an OCV-SoC curve is generated through experiments, forming a lookup table utilized in the model. Leveraging this OCV-SoC lookup table along with the Equivalent Circuit Model (ECM), the terminal voltage (V) can be computed by means of the subsequent formula:

$$V\ (t) = V_{OC}(SoC) - I(t)R - C(t) \quad (4)$$

where R is the internal resistance. the internal resistance serves as a representation of the electrical resistance present in different battery components, capturing the dynamics involved in the accretion and release of charge within the electrical dual-layer. Indeed, the author's assumption asserts that Voc, representing the open circuit voltage, is a function that is continuously differentiable. This implies that Voc as a function of SOC not only exists but also exhibits continuity without abrupt changes or discontinuities in its behavior across different SoC values.

Certainly, can particularly consider assuming Voc to behave as a Lipschitz function. Moreover, it's readily noticeable that $Voc(SoC) > 0$, $\forall SoC \in [0, 100]$. In this context, C represents a modification element accounting for model inaccuracies and eco-friendly factors, such as fluctuations in surrounding temperature. In order to determine this, it is necessary to combine the Thevenin-based ECM with a voltage hysteresis model. Using this approach, current-voltage appearances can be captured dynamically, while static current-voltage properties can be compensated for.

In this paper [11] , they choose for an Equivalent Circuit Model (ECM) incorporating a 2-RC circuit to strike a balance between computational demands and precision. A precise, user-friendly, and extensive electrical battery model is presented, incorporating an RC network similar to that of Thevenin-based models to pretend transient responses. Employing a voltage controlled voltage source, it establishes a connection between SOC and V_{OC}. This model amalgamates elements from previous models (Thevenin-based electrical model, runtime based electrical model, Impedance based electrical model), resulting in a unique blend of components and dependencies. This integration streamlines the extraction process, enables full compatibility with Cadence, and offers real-time and accurate predictions of runtime, transient responses, and steady state capturing the complete dynamic electrical appearances of batteries, including practical capacity (C Capacity), V_{OC}, and transient response (RC network).

In [12], a dynamic equivalent circuit model is introduced. This model incorporates a DC voltage source, a sequence resistance, and binary parallel RC networks. The DC voltage foundation emulates the battery's V_{OC}, the series resistance (R_S)

signifies the interior DC resistance, while the RC parallel grids (R_1, C_1, R_2, C_2) serve to depict the transient voltage feedback. The circuit model represents the terminal voltage as Vt. Incorporating the rate capacity effect, this model dynamically adjusts the usable capacity in response to changes in current. The SOC calculation relies on the usable capacity. Moreover, model's parameters are contingent upon both the SOC and the current, reflecting their interdependency. The terminal voltage of battery (V_t) is signified by a controlled voltage supply within this model.

In order to regulate the battery model's voltage value, five subsystems work in conjunction with one another: SOC computation, V_{OC} estimation, RC rates, Voltages of RC parallel networks, and VR_S. Furthermore, these subsystems are supplied with the current value for their operation by a Current quantity block. A SOC_0 represents the initial state of the system, whereas a SOC_n represents the state of the system in real time. The structure of each subsystem is explicated in the following sectors. The unique Shepherd model has a non-linear tenure equivalent to $K \frac{Q}{Q-\int idt} i$.

This term signifies a non-linear voltage that changes with both the magnitude of the current and the actual charge level of the battery. As soon as the battery is nearly fully discharged, and there's the current doesn't curving, the voltage of battery tends to increase, approaching approximately E_0. When current flows once more, the voltage experiences a sudden drop. Although this behavior reflects a actual battery, The mathematical model replicating this phenomenon introduces an algebraic loop, resulting in simulation lability. The suggested model addresses this by presenting a nonlinear voltage tied solely to the current battery charge. Consequently, when the battery approaches near-complete discharge without any current, the voltage tends toward nearly zero. This model not only produces precise outcomes but also accurately mirrors the battery's behavior [13].

The adopted Thevenin equivalent model for the Electrical Vehicle Battery (EVB) incorporates an open circuit voltage source. This source, contingent on the primary battery SOC, is linked in pairs with a Rs and a parallel RC subsection (Rt, Ct). This RC branch serves to depict the transient high voltage result. The terminal voltage of the EV is determined by amalgamating the V_{OC}, the voltage droplet crosswise the R_S, and the voltage droplet crosswise the RC.

The Nernst equation is used to establish the correlation between the Voc and the SOC of the EV in the following equation:

$$V_{oc}\left(SOC\right) = V_{nom} + s\,\frac{RT}{F}\,ln\left(\frac{SOC}{C_{nom} - SOC}\right) \quad (5)$$

The terms Voc(SOC), V_{nom}, and C_{nom} correspond to the Voc of the EV as a function of the EV (SOC), the nominal voltage of the EV, and the nominal capacity of the EV in Ampere-hours (Ah), respectively. While, s denotes the relationship between the sensitivity parameter Voc and SOC of EV. Moreover, R denote the gas constant , (F) refer to Faraday constant, and (T) resemble to temperature[14].

K.C. Syracuse and W.D.K. Clark applied numerical models to characterize the discharge performance of lithium-oxyhalide (LiOH) cells. Their study involved observing battery voltage standards at different periods of discharge while maintaining a consistent load and temperature conditions. Subsequently, they utilized a Weibull model comprising three factors to represent voltage in relation to sent capacity or else charge missing.

. Syracuse and Clark followed a comparable approach to estimate these factors for different load and temperature amalgamations, representing the difference of factors through a quadratic surface. Employing a akin technique, they forecasted battery lifetime based on both load and temperature variations. [15].

Massoud Pedram and Qing Wu, as outlined in reference [16], formulated a model for battery efficiency. This model represents the proportion of real capacity to theoretic capacity as a linear quadratic polynomial equation dependent on load current. It is possible to establish limitations on the real power expended across a wide range of current distributions, all of which possess a similar average current distribution. Their demonstration highlights that these limitations are contingent upon the extreme and smallest values of the current. When comparing distributions with identical means, a constant current distribution (minimizing variance) is predicted to extend battery lifespan the most, while a uniformly distributed current (maximizing variance) is projected to offer the shortest lifespan.

This model accommodates rate dependence and is capable of managing variable loads. Scientists have employed this model, often with minor adjustments, to optimize the longevity of multi-battery systems. Additionally, it has been utilized to reduce the discharge delay product within the framework of an interleaved double battery system design. Moreover, it has found application in stationary duty arrangement for actual time entrenched systems.

A theoretical model proposed by Carla-Fabiana Chiasserini and Ramesh R. Rao [17] shows charge retrieval as a function of state of charge and capacity discharged. Based on the assumption that every cell's load is pulsated, this model denotes discharge and retrieval as transient stochastic processes. Every discharge demand of i elements outcomes in a transition to I statuses minor, whereas respite periods induce public transitions consecutively toward larger states. Capacity expansion is articulated as $G = \frac{A_{cu}}{N}$, somewhere A_{cu} denotes the regular amount of charge components and N is the normal capacity of the charge extractible by a persistent load. The researchers utilized the Dualfoil emulator to generate curves depicting G as a occupation of the discharge degree across various load current density values. Two model parameters were then adjusted to align with these curves. This model proves beneficial in characterizing pulsed discharge, enabling the analytical calculation of capacity gains for diverse stochastic loads without reliance on simulation.

Chiasserini and Rao presented numerous analytical findings concerning load distribution between dual cells within a battery bundle. Nevertheless, since it distills one on charge retrieval, their model does not explain further battery non-linearities. Debashis Panigrahi and colleagues [18] additional a lookup table to integrate amount dependence.

3 battery estimation method

The SOC is a pivotal parameter that specifies a battery's residual current capacity, crucial for effective battery monitoring. The releasable capacity percentage is calculated from the battery's esteemed capacity [19].

Accurate definition of the SOC stands as a crucial aspect within BMS for EV. However, direct measurement of SOC is challenging because of the flatness and hysteresis observed in the V_{OC} curve, particularly in Lithium-ion chimerical such as LiFePO4. This impedes the direct measurement required for safety and optimal performance. The traditional method of current integration, known as Coulomb counting, faces challenges related to accumulative errors and inaccurate initial values in determining the state of charge. As a result, more sophisticated estimation algorithms are employed. A study of three model-based state spectator designs is conducted and analyzed to address these challenges: Luenberger spectators, Elongate Kalman Filters (EKFs), and Sigma Point Kalman Filters (SPKFs).. Dimension data obtained from commercial LiFePO4 cells is utilized to verify these estimation approaches. Computational tests are conducted to assess the system's performance, focusing on stalking accuracy, approximation robustness amidst temperature uncertainties, sensor gist, and conjunction performance when initialized with an SOC balance [20].

Coulomb counting and extended Kalman filter methods are used together to guesstimate the SOC of a specific battery. Depending on the kind of battery-operated, the model will change and one of the methods will gain more impact than the other. When comparing the battery voltage of a standard 12 V_{dc} lithium-ion and lead-acid battery in Figure 2, it's evident that the lithium battery exhibits a notably flat voltage response during continuous discharge. The voltage alteration occurs primarily when the battery is at full charge or fully discharged, leading to rapid changes.

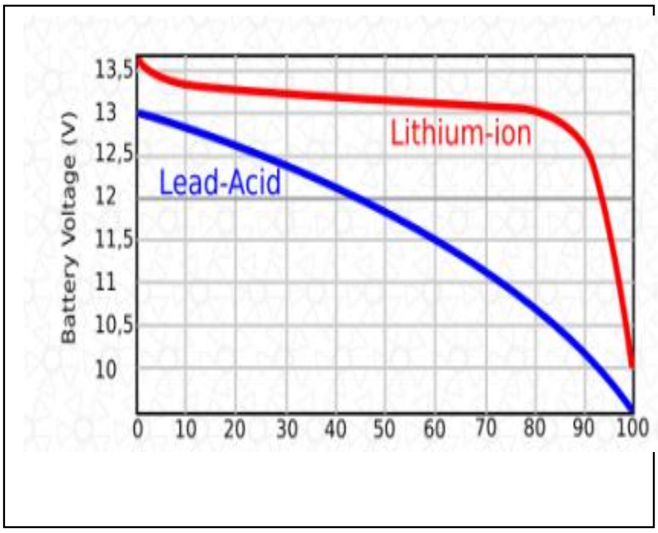

Fig. 2: Voltage evolution with Depth of Discharge

The Kalman filter benefits from its input of current, voltage, and temperature measurements, making it particularly effective in the flatter regions of the battery's operation. Conversely, Coulomb counting (CC) relies on a known (SoC) and the measured current, making it more suitable for application in the transitional or side regions of the charging/discharging curve.

Fig. 3: CAN - Battery Management System Interface for EPC family converters

Achieving a precise estimate of SOC is feasible, particularly in a non-linear battery (where SoC correlates with Voltage), even amidst significant levels of measurement inaccuracy. The necessary algorithms and processing for these calculations can be integrated into the "CAN BMS Interface" device, as depicted in Fig. 3, which receives inputs via CAN communication from the epic power EPC converters [21].

Nonlinear state estimation can be used to frame the SOC estimation issue. Kalman filter-based methods such as the extended Kalman filter (EKF), iterative Kalman filter (EKF), and unscented Kalman filter (UKF) are commonly employed for this purpose because they can reduce the effects of noise on batteries.

An alternative approach involves utilizing nonlinear observers such as adaptive observers, sliding mode observers, backstepping PDE spectators, and strong nonlinear spectators. These procedures are moderately informal to contrivance and thus allows larger computational efficiency of SOC guesstimate. The Extended Kalman Filter is composed of a nonlinear spectator with a linearized Kalman filter. By leveraging the strengths of together nonlinear state approximation procedures, it harnesses universal stability possessions from the nonlinear spectator and noise reduction capabilities from the Kalman filter. The process entails using the exogenic state approximation obtained from the nonlinear spectator to create a linearized model for the Kalman filter [22].

Built on the transfer function of the restrained battery voltage response to the charging current pulse, the paper [23] proposes a modern technique for assessing the SOC of LIBs. It's believed that the battery's transfer function alters with the SOC. A reference table is constructed during the learning phase, comprising known SoCs and their related transfer functions. These transfer function constraints serve as reference points in a multidimensional space.

When defining the unfamiliar SOC of the battery, Restrained transfer functions form a point in this space, enabling comparisons with known SoC transfer functions. In order to calculate the unknown SOC of a battery at a specific measurement time, it is necessary to identify the two closest situation points to the unknown SOC. In order to accomplish this, the geometry distance is calculated and linear disruption is used on the basis of this distance.

The article outlines a technique for evaluating the SOC using the battery model and its connection to the battery's dynamic response, often referred to as the battery transfer function. Based on the assumption that the voltage response functions are nonlinear functions of the SOC. The transfer function, describing how voltage responds to a current pulse at a specific SOC, helps define parameters linked to that SOC. These parameters, essentially representing coordinates in a hyperspace, can be measured to identify the characteristics of the transfer function for the associated SOC. As part of the education phase, a mapping was developed in order to correlate various SOC levels with their corresponding transfer functions. According to the method, an online quantity will be obtained of the battery's voltage response to a given current pulse to determine the efficiency of the system.

Subsequently, it computes the transfer function parameters. For an unfamiliar SoC, the transfer function's parameters method a new fact in hyperspace, allowing determination of the battery's SOC via interpolation based on the Euclidean detachment from nearby known points. The method's application is demonstrated by assessing the SOC of a large capacity lithium-nickel-manganese-cobalt-oxide ($LiNiCoMnO_2$) battery cell. Unlike other papers, this one does not require permanent measurements of battery voltages and currents - only the response of voltages to a three-second pulse of current. The algorithm may be applied in a charging station for a light electric vehicle battery without communication with the vehicle's battery BMS, which will be particularly important when it is applied in a charging station for batteries of lower electric vehicles that do not share a BMS.

4 Conclusion

Certainly, this paper delivers a complete overview of the primary research features within lithium-ion battery studies. It delves into critical areas like estimating battery capacity, sorting batteries, and predicting the remaining useful life of these energy storage units. And also represented the model used in Li-ion battery. we showed the paper that study recent advancements in addressing safety concerns related to lithium-ion batteries (LIBs) using materials chemistry. We highlighted key facts and underlying mechanisms concerning the safety issues of LIBs.

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