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Critical review of ageing mechanisms and state of health estimation methods for battery performance

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Abstract. Battery Management System (BMS) is an essential component for lithium-ion battery-based devices. It provides a variety of functionalities that help improve the overall lifespan of the battery, including states estimation algorithms. An accurate state of health is one of the essential features an advanced BMS provides, in order to track long term performance and ensure reliable operation of the battery.

This paper aims to provide a structured review of ageing mechanisms that affect the battery performance and also some of the most relevant algorithms that were used in the recent literature to predict the actual health of the battery. Finally, and based on the different approaches that were studied evaluation criteria are proposed to help judge the performance of State Of Health (SOH) estimation algorithm.

Keywords: Battery management system · State Of Health · Lithium-ion battery · Ageing mechanisms.

1 Introduction

To cope with climate changing and global warmth, communities have been promoting clean energy and they've been calling for a fossil-free society. According to the Environmental Protection Agency, 72% of carbon monoxide emissions come from automobiles only [1]. Thus, interest in electric vehicles (EVs) has grown fast.

Electric vehicles are much cleaner and cheaper to drive [2]. They usually use Lithium-ion batteries as an energy source, this type of chemistries presents the advantages of high energy density and low self-discharge compared with other rechargeable cells [4]. However, the capability to perform correctly and to store energy tends to decrease with time due to the ageing phenomenon. Therefore, Battery Management Systems (BMSs) are needed to boost the battery performance and improve its safety.

In general, BMS is an electronic system that controls and monitors the battery for safe usage and long lifespan. It has three basic tasks: data acquisition, battery states estimation and electrical management of the measured input to take action when needed.

In addition to cell balancing, battery modelling is a significant contributor to BMS reliability and performance. An accurate battery model is required to predict the battery behaviour under different conditions and to provide a proper estimation of the battery states [3].

Depending on the target application, the battery model can be represented using different approaches and can have different range of complexity. For electric vehicles, the battery model needs to be simple, computationally efficient and suitable for high discharge rates [4]. Thus, two main categories of battery models were presented in the literature. The first category known as Reduced Order Model(ROM) and the second category is the Equivalent Circuit Model(ECM) [5].

Reduced-order models are simplified version of electrochemical battery model [6]. The governing PDE equations that describe the electrochemical reactions inside the battery are approximated into low order systems of ODEs equations using a set of Model Order Reduction(MOR) techniques [7]. The most basic electrochemical model is known as Single Particle Model(SPM) [40], it represents each electrode of the battery by a single spherical particle ignoring thermal effects, approximating spatial and time characteristics at the separator region to 0 and assuming all unknown states to be scalar and uniform 1. SPM are simple and they can be adopted for real time applications, however, they lack accuracy at high C-rate. To overcome this limitation an extended version of these model that incorporates the electrolyte dynamics has been developed and they were proved to maintain a high accuracy prediction even at high C-rates conditions [8].

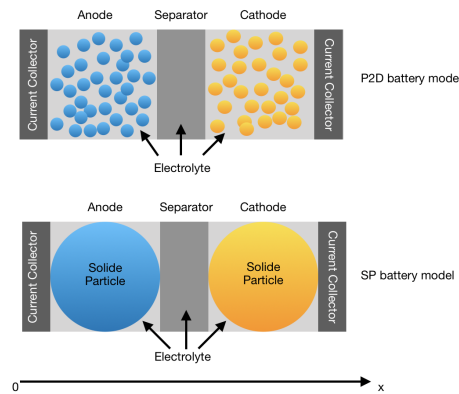


Fig. 1. P2D and Single Particle battery model

Another version that aims to reduce the computational burden of the P2D model was presented in the literature as the Simplified P2D model (SP2D), it describes the dynamic concentration profiles derived from the P2D model to help improve the accuracy of the BMS[9].

Equivalent circuit models on the other hand are widely used when developing a BMS for EV application thanks to their speed, simplicity and reasonable accuracy [10]. Starting by the most basic model that represents the battery as an ideal voltage source mounted on series with internal resistance to describe the voltage polarization, researchers have include different electrical components, in the interest of building improved versions which take into account the dependence of the battery cell on state of charge, temperature, and other characteristics[11].

The most used ECM for estimating the battery states for EV applications uses: an ideal voltage source, series resistance and one or more RC networks to simulate the behaviour of the battery under load (see figure 2).

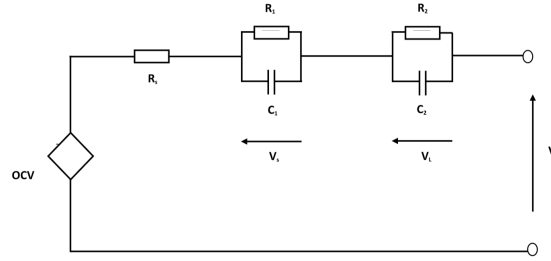


Fig. 2. Second order equivalent circuit model

Once the battery model has been decided, it can be used as an input for the states estimation algorithms whether it is the SOC, SOH or any other state.

Battery State of Charge (SOC) is one of the essential parameters a BMS needs to determine. It represents an instant indication of the battery status that estimates the percentage of the available capacity. On the other hand, the State Of Health (SOH), as its name implies, is a parameter that reflects the battery health and its ability to convey a specific performance compared with a fresh battery [13]. Having control over ageing causes can help reduce the degradation effects, but once the SOH hits a certain percentage the battery can no longer be used for electric vehicles [55].

1.1 SOH estimation in literature

Numerous surveys have been conducted in recent years to classify the SOH estimation methods [13–17]. In order to have a clear vision of the different approaches that were developed or improved in the literature, M. Berecibar et al. [13] presented a detailed classification of battery SOH estimation methods, that

arranges those approaches in two main categories depending on the way they were carried out. The strengths and weaknesses of each method were compared and analyzed, and the degradation mechanism was also presented. The authors of [14] review the estimation strategies and methodologies used in electric vehicles and classified them under three main categories that are: battery management related, vehicle energy management related and vehicle control related. Except for the battery state of charge(SOC), the rest of the estimation strategies are briefly discussed.

An extensive review of the methods for monitoring lithium-ion batteries in electric and hybrid vehicles is described in [15]. Based on an impressive 375 sources including technical and scientific literature, the estimation approaches for battery state of charge, state of health, capacity, impedance, available power and remaining useful life are provided.

Lucian Ungurean et al. [16] define a comprehensive, structured review of battery models and estimation methods used to determine the battery state of health. However, the ageing mechanisms of the battery are not presented. Same goes for Rui Xiong et al. [17] who provide a detailed presentation of battery SOH estimation algorithms with emphasis on their limits and strengths.

Before starting to define the state of health estimation approaches it's important to first outline the ageing mechanisms since, without having a clear insight of the ageing factors, we can not appropriately determine the battery health.

2 Ageing mechanisms

Degradation mechanisms affect battery health through reduction of total capacity and or expansion of equivalent series resistance, and observing those quantities that vary slightly and impact the battery performance as cell ages, is of great value to determine the battery state of health as accurately as possible.

Generally, unwanted side reaction and structural degradation that occurs inside the battery cell leads to capacity and power loss, and the complexity of the Li-ion based batteries makes the processes of their ageing at anodes and cathodes even more complicated [19].

Researchers have proved that ageing mechanisms at anodes differ from those at cathodes and their source can be either chemical or mechanical [20]. Therefore, the knowledge of these ageing processes is mandatory to control battery health as well as other parameters.

2.1 Ageing in the negative electrode

Depending on electrodes composition, safety properties and ageing ratio can differ from one cell to another. Therefore graphitic carbon materials are the most widely used as anode material, and thus, many research papers were devoted reviewing the ageing mechanisms of graphite-based anodes [21, 22].

Ageing effects can occur during storage just after manufacturing and during use, and can be observed at three different scales that are:

- **Electrode/electrolyte interface** :The main ageing factor that considerably affects the graphite electrode properties happens once the electrolyte comes into contact with the graphite, especially during the first charge inside of a battery manufacturing facility. The electrochemical stability window of the electrolyte does not include the voltages at which the graphite-based negative electrodes operate [24]. Hence a protective layer is developed as a result of electrolyte decomposition. Known as Solid Electrolyte Interface (SEI) [23].
Once it's formed, it encapsulates the graphite and blocks electrons from transport, to prevent any further electrolyte degradation [23]. The porous structure of this passivating layer allows the transition of Li-ion from the electrolyte to the particle, adding a resistance to the motion of Li-ion.
- **Within the electrode particles** : Ageing processes that occur inside the particles can have a minor negative impact on the electrode performance. The particles change volume when charging or discharging, due to the absorption and withdrawal of Li-ions[19], leading to structural changes that can cause particles to crack and be less ordered compared to the original structure, which enables further SEI growth and active material loss[28].
- **Composite electrode** : Volume changing affects the electrode porosity that facilitates the penetration into the bulk of the electrode. It is also considered as the main reason for the loss of contact between active cathode particles, that can be accelerated when over-discharging the battery cell, resulting in higher cell impedance and capacity loss [29].

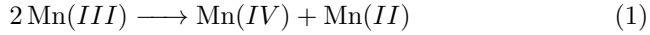
2.2 Ageing in the positive electrode

Aging can also occur at the positive electrode and can affect battery performance, and as for the negative electrode the chosen material impact significantly the battery performance. In terms of performance cost and abundance, most Lithium-ion battery cells use Lithium manganese oxides with spinel structure and lithium nickel cobalt mixed oxides with layered structures as the cathode material. An aged positive electrode material can have different effects that can be summarized as [30]:

- **Film formation**: The electrolyte oxidization and the decomposition of the electrode particles form a film layer called Solid Permeable Interface(SPI) that has different composition and properties from the anode SEI [31]. High temperatures induce the dissolution of metals from the electrode into the electrolyte accompanied by CO_2 gas evolution breaking down the overall crystal structure of the electrode leading to capacity loss[19].
- **Loss of active material**: The intercalation of lithium into the crystal structures of the cathode active materials causes mechanical stress that leads to strains of the metallic oxide particles and variation of their molar volume. These distortions are known as a phase transition. They are often reversible, and they proceed as lithium ions are inserted/extracted in/from the positive electrode. The most used lithium-ion battery cells have a structured

layer, therefore when the battery is overcharged the lithium particles that hold these layers apart are extracted and the layers can fall on each other reducing lithium storage sites and causing capacity loss[36].

- **Metal dissolution** : The dissolution phenomena of the metal from the electrode into the electrolyte results in capacity loss and can re-precipitate on the surface as a high-resistance film. The dissolved manganese particles moves to the anode and merge into the SEI interface enhancing the self-discharge of the battery cell. In general manganese dissolution can occur at low-potential, where trivalent manganese ions disproportionate into tetravalent and divalent ions, or at elevated potential known also as acid dissolution accelerated by hydrofluoric acid.



Battery cells age even when they are not used. Ageing can be separated into calendar ageing that represents degradation caused by battery storage, and cycle ageing that occurs when charging or discharging the battery.

3 Health estimation

The estimation of the battery state of health is usually associated with the determination of two essential indicators that are battery capacity and internal resistance, which respectively reflect the energy and power potential of the battery cell[34, 35]. Different algorithms and processes can be applied to these parameters to track the degradation of the battery, and for better understanding of the performance of each approach, literature has proposed different classification for these methods.

3.1 Internal resistance

Internal resistance stems from the fact that a battery is not an ideal voltage source. It represents a direct indicator of the battery health that serves to spot any defects tending to damage the battery, and that explains the interest of researchers to measure this parameter.

Ageing causes the battery to lose its capacity and increase its internal resistance. Jinsong Yu et al [32], define the battery internal resistance based on changes in the voltage curve while applying a discharge current, and by using Ohm's law, the internal resistance can be approximated as follow:

$$R = \frac{\Delta U}{\Delta I} \quad (2)$$

Where ΔI represents the current step-change and ΔU is the corresponding voltage to the same step-change.

The internal resistance was proven to change with different factors such as battery size, chemistry, temperature and other parameters. Yingjie Chen et al

[33] considered that the battery internal resistance depends on the state of charge (SOC), the current rate and temperature, they conducted a constant current test under different temperatures to provide continuous R-SOC results.

3.2 Impedance Spectroscopy method

Battery impedance also is another parameter that we can use to determine the battery health, it comprises of impedance commitments from battery sub-components (current collector, electrode and separator) and association between these sub-components. For example current collectors and separator can be viewed as complete resistive components, while impedance in electrodes comprised charge transfer, diffusion and contact resistance [36]. Using electrochemical impedance spectroscopy, we can determine the actual value of this parameter, the reliability and of this method has motivated many researchers to estimate the battery states and also to predict the parameters of an electrochemical battery model [37]. However, since EIS is usually used with an equivalent circuit model to determine the battery state of health, the results are affected by the modification of the battery model due to ageing [38].

3.3 Coulomb counting

Another way to estimate the battery SOH is by tracking the amount of charge that flows in or out during the charge-discharge process [16]. It first calculates the capacity at discharge by integrating the value of discharge current in time, so a high precision current sensor is needed, then it uses this value to compute the SOH as follow:

$$SOH[\%] = \frac{Q_{max}}{Q_{nominal}} \times 100 \quad (3)$$

where Q_{max} is the maximum available capacity and $Q_{nominal}$ is the measured capacity. the accuracy of this approach requires high monitoring and storing capacity and a high-precision current sensor. Being not affected by the temperature, DOD or C-rate gained her wide popularity among methods that estimate the battery SOH and also SOC [13].

3.4 Kalman filtering

Kalman filtering is a sturdy algorithm that was used over history to estimate battery parameters and states. It's defined as an adaptive method that operates in two steps [13], first, the algorithm predict the current output variable, then, the estimation is updated to obtain more accurate results (3).

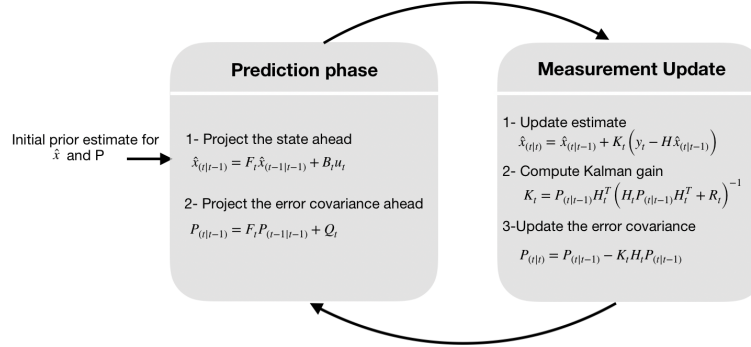


Fig. 3. Process of kalman filter

Where \hat{x} is the estimated state, F is the state transition matrix, B is the control matrix, u is the input vector, P and Q are respectively the state and the process variance matrix, y is the output measurement, K is the Kalman gain, H is the measurement matrix and R is the measurement variance matrix.

Kalman filter can operate properly only when the system is linear, however, to deal with nonlinear systems extensions of this method have been developed such as extended Kalman filter (EKF), unscented Kalman filter (UKF), adaptive EKF(AEKF), dual extended kalman filter (DEKF) etc. [16].

Extended Kalman filter Extended Kalman filter is used when the transition and the measurement equations are not linear. A linearization process is applied at every time step to approximate the nonlinear system with a linear time-varying system (LTV)[46]. The algorithm was widely used for battery modelling and states estimation [47, 48] thanks to its accuracy and speed.

In [49], the authors use a combination of extended Kalman filter and EIS algorithm to estimate the battery internal resistance and capacity to provide reliable information about its remaining stored energy.

[50] perform a co-estimation of battery SOC and SOH using Lebesgue sampling based extended Kalman filter (LS-EKF) to reduce the computation cost when the states change slowly. The SOH and RUL were first predicted using LS-EKF. Then the obtained results are used to estimate the battery SOC.

Dual Extended Kalman filter As the name suggests, Dual extended KF (DEKF) is a combination of two extended Kalman filter that synchronously estimate the battery states and parameter [46] (see figure 4). N. Vassiliadis et al. propose a use-case life cycle analysis of DEKF for battery SOC and SOH prediction. The paper investigates the performance of the DEKF algorithm including different SOH stages and load dynamics. A comparison of the performance of DEKF versus a simple EKF shows a partial improvement in SOC accuracy.

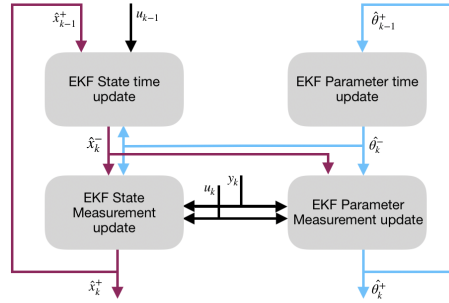


Fig. 4. DEKF Structure

The authors of [51] propose a combination of charging voltage curve and DEKF algorithm to estimate the battery SOC. The transformation of the charging voltage curve is used to determine the battery internal resistance and capacity, then DEKF algorithm is used to estimate the battery SOC. The results of this combination show an improvement in accuracy and elimination of the measurement noise.

Unscented Kalman filter Unscented Kalman filter also known as the sigma point Kalman filter is an algorithm where the state distribution is specified using a minimal set of carefully chosen sample points [52]. Unlike the EKF that loses its accuracy when dealing with highly nonlinear systems, the UKF uses the true nonlinear models to estimate the results as accurately as possible [53].

[54] used the UKF approach to predict the battery SOC, internal resistance and capacity, based on an improved Equivalent Circuit Model (ECM). The method was also used to evaluate different battery states(SOC, SOH, SOF), and was proved to be timesaving and efficient.

3.5 Fuzzy Logic

Fuzzy logic is a mathematical concept that models complex nonlinear systems and solves uncertainties in a given problem. The method uses crisp sets or fuzzy sets that allow elements to be in a set with a degree of membership. A membership function is used to define the relationship between a member of a set and its degree of membership that range from 0 to 1 [39]. Taking the battery state of health as an example, we can define the membership functions outputs as healthy, tolerable and not healthy.

In [40], the author uses a fuzzy logic-controlled methodology to predict the battery SOH, the process is divided into two parts, first the cell resistance and maximum capacity are determined based on voltage, current, temperature and time, Second using the resistance and the maximum capacity values SOH can be predicted by applying fuzzy logic.

State of health estimation of Li-ion battery based on a fuzzy-logic system was also presented in [41], using temperature and the absolute value of the current the fuzzy logic system is constructed, which enhances the SOH value on both the calendar and cycling life.

3.6 Support vector regression algorithm

The support vector regression algorithm is a nonlinear generalization that implements a structural risk minimization principle to get a good generalization on a limited number of learning patterns [42]. It adopts the original machine learning algorithm to predict the output of a given input.

In [43], the authors used a novel support vector regression that takes the battery capacity as a state variable, and constant-current and constant voltage as an input variable of the system to predict the battery SOH. Furthermore, the model was combined with a particle filter to reduce the errors caused by measurement noises and to provide more accurate and robust result.

Duo yang et al [44]. proposed a novel SOH estimation approach. They started by building an improved battery model, which combines OCV modelling and Thevenin equivalent circuit model (ECM). The battery SOC was estimated using the joint extended Kalman filter-recursive-least squares algorithm. Then a reliable SOH estimation result was obtained using a combination of the support vector regression approach and the particle swarm optimization algorithm. The authors of [45] used Support Vector Machine (SVM)/Support Vector Regression (SVR) for classification/regression with less experimental data compared with the neural network. The SVM was used for battery classification and then they used SVR to estimate the remaining useful life of the battery.

3.7 Least squares

The least square algorithm is a widely used procedure to estimate the parameters of a given system. The basic problem is to identify the best fit function that minimizes the sum of errors between measured output and system response. To estimate the battery SOH, Gregory L.Pett [55] used an improved version of the RLS algorithm called the Weighted Total Least Squares estimation approach (WTLS). The author started by identifying the main drawback of using a standard least squares approach to estimate the battery health. Since this method doesn't take into consideration the uncertainty that we have on the input measurements (SOC) the author uses WTLS approach to determine the battery health with knowledge of both noises on the accumulate ampere-hour measurements and on the battery SOC. The method shows better results compared to a standard least squares algorithms and it's suitable for real-time implementation.

3.8 Evaluation criteria

The previous section has presented some of the recent commonly used approaches in the literature to estimate the actual health of the battery. The accuracy of

the predicted SOH is a significant parameter that authors try to prove. However, this parameter only is insufficient to evaluate the estimation algorithm results. Thus we propose some criteria that can be used to judge the performance of a given algorithm:

- *Battery model*: When using an algorithm that predicts the battery states based on a specific battery model, the result precision can differ since some models lose their accuracy with the use, due to different ageing mechanisms.
- *Computation cost*: it's an indication of whether the proposed approach is suitable for a real-time application, in another way if the method can be implemented in a BMS running an embedded system.
- *Time cost*: it defines the duration of the execution, the time needed to provide the result, which depends on the complexity of the algorithm and also the hardware specification.
- *Estimation precision* an indication of the calculation error, how much the result diverges from the actual one.

An extensive comparison of health estimation algorithms is presented in [13]. The author concludes that there is no unique or perfect method to estimate the battery health. The choice of method should be selected based on the target application, what's needed to be estimated and how much error tolerance is acceptable.

4 Conclusion

Lithium-ion batteries have been widely used as the main energy storage solution for EVs. To make the most of this technology, BMS was used to manage the battery performance and ensure the safe operation of the cells.

State of health estimation is a crucial parameter that helps batteries operate in a safe condition. This review presented the aging mechanisms that affect the Lithium batteries during their life to help build a basic understanding of the different factors that accelerate the process of aging and cause capacity fading. A description of the most relevant methods that were presented in the literature to estimate the battery internal resistance and capacity are provided, the review shows that there is no perfect health estimation algorithm and that the choice should be made based on the target application. Finally, the author proposes some evaluation criteria that can help judge the performance of the health prediction algorithm.

Acronyms

AEKF	Adaptive Extended Kalman Filter.....	8
BMS	Battery management system	1
DEKF	Dual Extended Kalman Filter.....	8
ECM	Equivalent Circuit Model	2
EIS	Equivalent Impedance Spectroscopy	7
EKF	Extended Kalman Filter	8
EV	Electric Vehicle	1
HEV	Hybrid Electric Vehicle.....	6
LS-EKF	Lebesgue sampling based Extended Kalman Filter.....	9
LTV	Linear Time-Varying	9
OCV	Open Circuit Voltage	10
P2D	Pseudo two dimensional.....	3
ROM	Reduced Order Model.....	2
RUL	Remaining Useful Life.....	9
SEI	Solid Electrolyte Interface.....	5
SOC	State Of Charge	3
SOF	State Of Function.....	10
SOH	State Of Health.....	1
SP2D	Simplified Pseudo two dimensional	3
SPI	Solid Permeable Interface	5
SPM	Single Particle Model	2
SVM	Support Vector Machine	10
SVR	Support Vector Regression.....	10
UKF	Unscented Kalman Filter.....	8
WTLS	Weighted Total Least Square.....	11

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