A Review of Lithium-ion Batteries Diagnostics and Prognostics Challenges

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***Abstract*—Battery technology besides its importance and exceptional characteristics is not still a mature technology and there is a real need for research and innovation in their lifetime, charging rate, second use, etc. The dependency of our daily lives on batteries is irrefutable and they are becoming growingly ubiquitous in our daily lives. Battey performance is degrades with battery aging and therefore a battery diagnostics and prognostics tool to enhance the effective use of the battery system is necessary. This paper deals with some challenges that remain unsolved in battery diagnostic and prognostic techniques. A review of recent battery diagnostic approaches for battery state estimation is performed and their relative advantages and disadvantages are emphasized while comparing the available methods to predict the battery end of life (EOL) or remaining useful life (RUL) as a key tool in battery prognostics.**

Keywords— Diagnostics, Lithium-ion Battery, Prognostics, Remaining Useful Life, State of Charge, State of Health

I. Introduction

Battery storage technology especially lithium-ion battery is an important part of the puzzle of energy transitions especially considering the burning need for a solution to mitigate the ramifications of climate change [1].

Lithium-ion batteries, due to their superb performance in energy density, power density, lifetime, and columbic efficiency in comparison with lead-acid, nickel-metal hydride, and nick-cadmium batteries are more desirable [2]. Commercial-scale Li-ion batteries have improved over the years in their specific energy and envelope an extensive range from 90 to 250 Wh/kg which is much better than the specific energy of lead-acid batteries, which is typically around 50 Wh/kg [3].

To guarantee a safe and reliable operating condition for a battery pack, each pack must be tailored with a battery management system (BMS) [4]. BMS can protect the battery pack against abnormal situations by controlling the charge and discharge cycles and performs measurements to increase the battery durability. The main functions of a BMS are cell and pack monitoring, charge and discharge control, cell balancing, thermal management, cell and pack protection, and battery state estimation [5].

Battery state of charge (SOC) is a quantity that describes the stored charge capability of the battery and battery state of health (SOH) is a quantity describing the ageing level of the battery. Unfortunately, battery SOC and SOH are not directly measurable values. The accuracy in SOC estimation is important to make the best effective use of the battery system, to improve battery lifetime and safety by protecting the battery from overcharge or under discharge. Also, battery SOH is an indication that illustrates the battery capability to store power and energy. It can be defined as a comparison between the battery capability at the beginning of its life and the current operation condition of the battery. There are multiple definitions of the SOH according to the capacity or internal impedance of the battery and a poor SOH indicates degradation of the battery during the time.

Due to the battery performance decrement over the battery lifetime, a battery diagnostic and prognostic system must be developed to enhance the effective use of a battery pack. SOC and SOH are two important parameters in battery diagnostic and battery lifetime expectation, while the remaining useful life of the battery can be investigated in battery prognostic.

This paper is structured as follows, in section II, the battery SOC, and SOH estimation, as two of the most important parameters in battery diagnostics has been investigated. In section III, the most prominent approaches in battery health prognostic to predict the RUL of the battery and their relative advantages and disadvantages have been discussed. Finally, in section IV the main challenges in battery diagnostics and prognostics with some key information from the literature review have been proposed.

II. Battery Diagnostics

To use the battery at an acceptable safety level with high reliability, an accurate estimation of battery SOC and SOH is necessary. The key issue for both estimations comes from the point of battery nonlinearity and time-varying nature during its operation (charging/discharging). The battery performance is really dependent on the dynamic battery operation condition and it is difficult to determine accurately the battery chemical process [6]. Consequently, it becomes obvious that the estimation of the battery states like SOC and SOH are challenging and many environmental conditions(temperature, pressure, humidity, ageing process, …) can affect estimation accuracy. An unreliable estimation can lead the battery to abuse operation conditions that can result in fast battery degradation and in the worst case, even cause an explosion within the battery system. Battery SOC and SOH are two important parameters in battery diagnostics and monitoring systems. In Fig. 1, different methods for estimation of these two parameters have been categorized. Both parameters are not directly measurable, and the estimation is based on measurable parameters such as terminal voltage, current, and temperature.

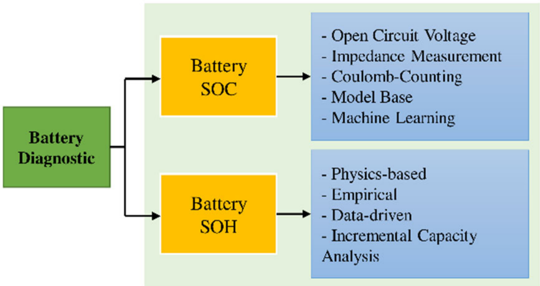

Fig. 1. Classification of different battery diagnostics tools for estimation of SOC and SOH considering both direct and indirect methods of SOC estimation and the entire spectrum of SOH estimations

A. Battery State of Charge Estimation

An accurate estimation of battery SOC will prevent the battery from overcharging/under-discharging and yield a better lifetime by reducing the battery ageing factors. In recent years many researchers from different points of view have proposed diverse methods for battery SOC estimations. The key challenges to accurate SOC estimation are battery nonlinear ageing process and complexity of battery chemistry, The key parameters that are important to the battery ageing process are temperature, over-voltage, under-voltage, over-current, undercurrent, etc. Various types of SOC estimation methods have been proposed in literature and most of them have employed different battery electrochemical and/or electrical models by using mathematical and estimation tools.

In general, the methods that have been used for SOC estimation can be categorized as direct approaches and indirect approaches. In traditional methods, the battery SOC is estimated according to one of the measurable parameters like voltage, current, impedance, or temperature, and thereby enabling battery SOC estimation. Even though these traditional methods have the advantage of low calculation burden but they suffer from low accuracy. In addition, Li-ion batteries due to their flat open-circuit voltage (OCV)-SOC curve further adds to uncertainty in SOC-Voltage correlation.

The indirect methods also are classified into two approaches, model-based and machine learning ones. Fig. 2 displays a schematic of battery model based on SOC estimation. In this method, the estimation is done according to the battery's measurable values like the voltage, current, and temperature by employing an appropriate and accurate battery model.

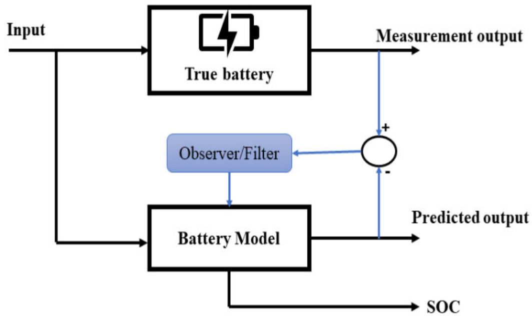

Fig. 2. Simple schematic of a model-based SOC estimation method based on sensor readouts of temperature, voltage, etc. with feedback-based modeling [7]

The main idea is to set up a relationship between the measurable value of the battery as an input and the SOC by using a battery model, As a result, the estimation accuracy in this method is very dependent on the battery model [8].

Due to the complex chemical reaction taking place inside the battery, the dynamic behavior of the battery system is intricate and still, there is a shortcoming about all the physical and chemical phenomena in action inside the battery system that is directly related to the accuracy of estimation in model-based approaches.

In Machin Learning (ML) approaches despite sufficient knowledge of the chemistry and physics of battery systems, and only by using the training data an approximate relationship between input and output of the battery system can be extracted [9]. With extensive training data, the model can replicate the real-world operation conditions of the battery system with high accuracy of estimation. As a result, if the battery operation condition is beyond the limits of the training data set, the result in estimation would not be accurate [10].

Different methods bring different levels of accuracy with different levels of complexity. In order to find an optimal balance between accuracy and complexity as shown in Fig. 3, the preferred method is application dependent and the choice dictates a fine balance between the two parameters.

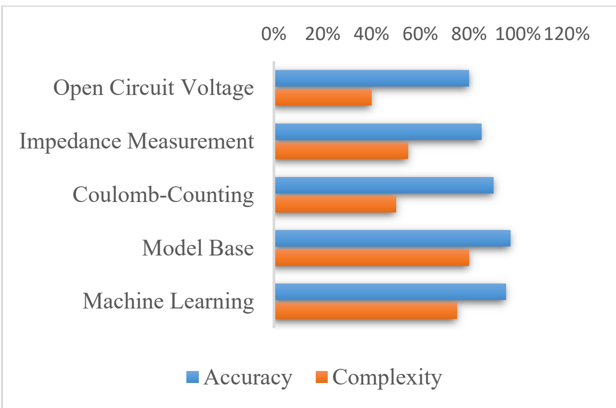

Fig. 3. Comparison between different methods for SOC estimation in terms of accuracy and computation burden

A brief comparison between the different methods for battery SOC estimation is summarized in table 1.

Table I. SOC estimation methods comparison

Methods	Advantages	Disadvantages
Open Circuit Voltage [11] [12] [13]	The easiest method for SOC estimation, Linear dependence between battery OCV and SOC	Need to have a rest period before OCV measurement, low accuracy especially for batteries with flat OCV-SOC curve, not suitable for onboard SOC estimation
Impedance Measurement [14]	Simple method for SOC estimation, applicable for onboard SOC estimation	Low accuracy, not suitable for batteries without significant change in their impedance with SOC
Coulomb-Counting [15][16]	Easy implementation, applicable for onboard SOC estimation but not ideal	Low accuracy especially after a long period, initial SOC value is needed, high accuracy current sensors are needed to minimize cumulative error
Model Based [8][17][10][18][19]	High accuracy, applicable for real-time application, robust to unknown initial SOC value and noise measurement	High complexity of the electrochemical model, accuracy of the SOC estimation completely depends on the accuracy of the model
Machine Learning [20][21][22]	High accuracy, appropriate for real-time application	Accuracy completely depends on the quality and amount of the training data, High complexity, and high computational time

B. *Battery State of Health Estimation*

Battery SOH as a diagnostic measure is one of the key parameters of the battery, that is estimated according to the battery measurable parameter. Normally the battery SOH is defined as the battery's maximum capability to store and deliver electrical energy compared to a fresh battery. Substantially, battery SOH methods can be categorized into four categories, i.e., physics-based models, empirical models, data-driven methods, and Incremental Capacity Analysis (ICA) based methods [22].

Physics-based model comprises of partial differential equations (PDEs) to describe the diffusion, migration, and reaction kinetics inside the battery [23]. These models need comprehensive knowledge about the physics and chemistry of the battery and have a high accuracy in battery state estimation. By fitting experimental data gathered under predefined experimental conditions, battery empirical models will be obtained [24]. This model completely depends on the experimental data and the accuracy in this model is related to the fact that how much the experimental test is close to the real battery operation condition.

Data-driven methods for battery health estimation are becoming one of the most leading approaches to battery SOH estimation due to the important factor that they do not involve the battery complex physics model in their estimation and flexibility. Like SOC estimation here the methods need a large set of aging data and the method effectiveness is completely dependent on the amount and quality of the data [25].

The incremental Capacity Analysis method is a powerful tool for online SOH. This method is based on the differentiation of the battery capacity over the battery voltage, estimation in this method can be easy to implement by monitoring only voltage and charge/discharge capacity [26][27]. A brief comparison between the different methods for battery SOH estimation is summarized in table 2.

Table II. Comparison of different SOH methods adapted from [22][26]

Methods	Advantages	Disadvantages
Physics-based models	High accuracy	High complexity, high computational effort
Empirical models	Simple structure, Easy to implement	Low accuracy and robustness
Incremental Capacity Analysis	Easy to implement, applicable method for different types of batteries, easy to monitor (voltage and capacity)	Significant demand for voltage and current measurement, sensitivity to operation temperature
Data-driven methods	High accuracy, appropriate for real-time application, model-free approach	Dependent on the amount and quality of training data, high computational burden

III. BATTERY PROGNOSTICS

Due to the electrochemical side reactions in anode, electrolyte, and cathode, battery degradation is a complicated problem. Find an accurate approach to determine the battery's end of life or remaining useful life in different operating conditions is very critical. Generally, the time when the battery reaches the failure threshold for the first time has been defined for the battery's remaining useful life[28]. Operating conditions even in the simplest charge and discharge of the battery, have an impact on degradation conspicuously and hence the battery lifespan.

RUL methodologies by using gathered data including that of battery performance can predict the future states of the battery and forecast battery failure before it occurs. Hence, an accurate estimation about the period for battery replacement or the moment for action to repair and maintain the same can bring about a reliable and safe operation for the battery. In addition, it has a significant effect on the economy of battery-powered systems [29].

Generally, the battery RUL prediction method can be categorized into model-based and data-driven approaches. As mentioned before, most of the model-based approaches, especially the electrochemical model for battery lifetime estimation, are dependent on the electrochemical reactions inside the battery. Since the battery has a time-varying and nonlinear dynamic electrochemical process and each discharge cycle depends on complex calculations of several parameters [28], it can be concluded that accurate degradation theory-based prediction is almost impossible. In addition, apart from several parameters, each battery pack consists of cells that are connected in series and parallel. Further, the chemical and physics interactions of each individual cell in a pack, if modeled will lead to the highest accuracy but with increased complexity. On the other hand, to overcome these challenges, data-driven approaches have been proposed recently in literature. A spider chart to compare the different battery health prognostics tools is shown in Fig. 4.

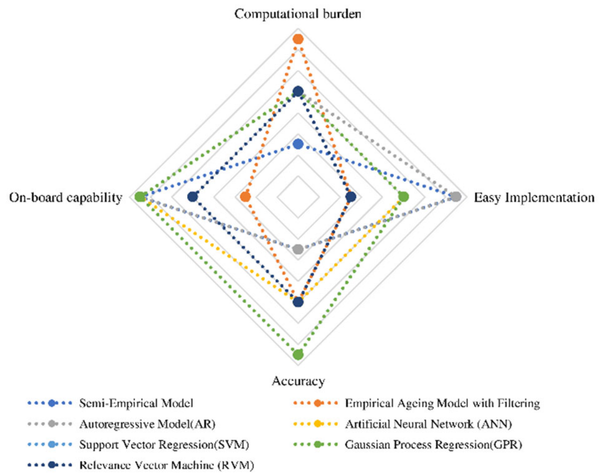

Fig. 4. Spider chart for Li-ion battery health prognostics methods comparison adapted from [26][30], where several important criteria have been compared

The data-driven approaches are normally model-free and the method is on the basis of data from manufacturers performed under different charge and discharge conditions. With developments in advanced algorithms for processing data and large volumes of data, the model assumes higher accuracy in a computationally efficient manner.

IV. Conclusion

Battery accurate states estimation especially SOC, SOH estimation, and RUL prediction are still unsolved problems due to the battery's complicated electrochemical dynamic. An optimistic or pessimistic estimation can have a result in battery underutilization or even lead to abuse operation conditions. This paper presents a state-of-the-art review of battery diagnostics and prognostics. In battery diagnostics, SOC and SOH are the key states of the battery system the main challenges and the most prominent approaches for their estimation have been reviewed. In battery health prognostics the battery remaining useful life (RUL) prediction is the most important parameter and the most common approach for RUL prediction according to their advantages and disadvantages have been investigated. Some important information related to battery diagnostics are summarized as follows:

1. Battery electrochemical model is the most accurate method for battery state estimation subject to varied operation conditions. However, electrochemical models are limited in utility because a full-order model needs comprehensive knowledge about cell chemistry and it requires a high computational effort.
2. Battery electrical circuit models are really practical due to their high computational efficiency for battery SOC and SOH estimation but unfortunately, they are less accurate. Employing an appropriate equivalent circuit model can increase the battery estimation accuracy.
3. The amount and quality of training data is the most important factor in ML methods, as the data gets closer to the real battery operation conditions, the result gets more accurate.
4. According to the application, a trade-off between accuracy and computational efficiency is essential to hire the appropriate estimation method.

An accurate RUL prediction is a critical responsibility for energy storage system design. Some important information regarding the battery health prognostics are summarized as follows:

1. Battery SOC and SOH estimation accuracy are important for battery remaining useful life.
2. Battery End of Life (EOL) can be defined according to their performance during the operation or by the cycle counting method
3. The loss of lithium inventory (LLI), increase of cell internal resistance and loss of active material (LAM) are the three main degradation modes in Li-ion batteries.
4. Depending on application, only important factors should be considered for simplification of life estimation models, for instance in solar home systems the increment and decrement of battery C-rate is normally at a slow rate, but the battery Depth of Discharge (DOD)is critically important.
5. In data-driven approach, it is really important that the operation condition is in the same region of training data. Improving the experimental testing and algorithm can increase the data-driven approach's reliability.

Based on research experience and the performed literature review, the main challenges in battery diagnostics and prognostics are described as follows:

1. Most of the approaches for battery states estimation have been performed on a cell level, battery diagnostics, and prognostics at a module and pack level are still challenging.

2. The battery reliability is dependent on each individual cell, if a cell fails the pack is not functional anymore.
3. The degradation behavior of Li-ion cells is sensitive to the operating conditions, it is difficult to predict ageing process under conditions different from the training dataset for ML approaches.
4. A trade-off between the accuracy, computational effort and generalizability for each application is still challenging but essential for optimal estimation.

FUTURE WORK

In the future, it is expected that combining model-based methods with ML methods provide critical information about the battery ageing mechanism in play. This is still rather challenging, however, the expectation is that the accuracy of the battery state estimations can reach a maximum by employing such a hybrid approach.

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