A Comprehensive Review of State of Charge Estimation

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Abstract - Modern energy storage relies predominantly on lithium-ion batteries, thus requiring a dependable Battery Management System (BMS). One of the most demanding BMS tasks is estimating the battery's State of Charge (SOC), which is estimated indirectly using voltage, current and temperature readings. This article reviews techniques that are currently utilized for estimating SOC such as Direct methods, model-based techniques and data-driven techniques. The article will evaluate and discuss the traditional and hybrid methods, strengths and weaknesses of each technique. This paper Summarizes the key gaps which are identified to full fill the SOC estimation.

Key Words: Lithium-Ion Batteries, State-of-Charge, Battery Management System, Kalman Filter, Machine Learning, Deep Learning

1.INTRODUCTION

The world is transitioning from traditional fossil fuels to sustainable energy solutions (like solar and wind) and transitioning to electric transportation, which is driving demand for more robust and energy-efficient methods to store power. The most popular energy storage method (out of many types of electrochemical systems) is lithium-ion batteries because they have very high volumetric energy densities, high gravimetric energy densities, very low self-discharge rates, and last longer than any previous generation energy storage; lead-acid, nickel-cadmium, etc. While the risks associated with lithium-ion batteries increase as a system scale from small cells in consumer electronics to commercial level energy storage applications (grid) and electric vehicle fleets, in order to fully capitalize on lithium-ion batteries, proper implement contactor-controlled Battery Management Systems is paramount.

Determining state-of-charge (SOC) for lithium-ion batteries is one of the most challenging tasks a BMS has to perform. This is due to the internal complexity of +5,000+ different electrochemical reactions, the time-dependent nature of these electrochemical systems, and the number of internal non-linearities preventing accurate measurement of SOC (as would be done to measure liquid fuel in a tank). As a result, there has been a great deal of research and development of realistic state of charge (SOC) estimation algorithms, crossing disciplines such as chemical engineering, control theory and computer science. To appreciate the complexity inherent in SOC, on must first have an understanding of the basic operation of lithium-ion batteries as follows. In the lithium-ion battery, when discharged, lithium ions leave the anode (negative terminal) and make their way to the cathode (positive terminal) of the battery through a liquid or solid electrolyte, producing electrical energy to supply power to an external load (by releasing electrons). Charging the battery reverses the above-described process. SOC is defined as the available capacity of a battery as a percentage of the nominal capacity of the battery (that is, 100% SOC means the cell is fully charged and 0% SOC means the cell is fully discharged). SOC is a "hidden variable," in that it represents the internal electrochemical status of the battery (specifically, the concentration of lithium ions located at the active material at both anodes and cathodes) and cannot be measured with a conventional meter (voltmeter or ammeter). Accordingly, the battery management system (BMS) must estimate SOC by estimating the state of the entire system using external inputs (e.g., voltage, load current and temperature). As an example, Terminal Voltage (i.e. Open Circuit Voltage (OCV)) is directly proportional to both SOC (State of Charge) and OCV but, to accurately obtain an OCV, a battery needs to be at rest for a certain amount of time which allows the battery cells to fully interconnect and stabilize their states; therefore, there has been developed a new way to calculate these values, (e.g. continuous real-time calculation) by continuously computing electrical signals into mathematical representations for the dynamic electrical signal into the internal electrochemical states of the battery.

2 PROBLEM STATEMENT

SOC estimation technology suffers from the time-variant, non-linear behavior of Li-ion battery systems when in dynamic conditions. Centrals to the accurate estimation of SOC are terminal voltage, current and SOC, and how they can be mapped with each other (functional mapping). Current voltage and SOC can be mapped together; however, the mapping of voltages and SOC will vary considerable at any given instant by ambient temperature as well as C-rate (charge-discharge rate). In addition to this, batteries will continue to degrade over time through the use of them (100s of cycles), with higher internal resistance and reduced capacity being experienced. As a result, static estimation models of SOC become invalid due to the increased rate of estimation error. In addition to this, the number of processors used in a basic battery management system causes a large amount of measurement error due to the use of low-cost sensors used within basic battery management systems. For these reasons, it is extremely difficult engineering to create an estimation algorithm for SOC that is accurate, adaptive to battery degradation, resistant to sensor noise, and has low computational requirements for microcontroller platforms.

3. LITERATURE REVIEW

Based on the developing field of SOC estimation researchers have established numerous publications documenting this progression occurring from lower-level heuristic-based estimation approaches to higher level algorithmic methods [10, 14]. The published studies related to SOC estimation can be grouped into three major categories as per previous literature review work: Direct Measurement Techniques (Traditional) , Model Based Filtering Techniques (Galvanostatic) , and Modern Data Driven Techniques [1, 2, 17].

Direct Measurement Techniques, which have evolved over time and evolved continually over time, were considered as the first developed techniques to estimate SOC directly by measuring SOH. Of these methods the commonly referred to Integrated Method of SOC estimation via Ah or Coulomb Counting are generally utilized due to their low computational complexity and ease of calculation [1, 2] . In simple terms researchers calculate the sum of all current entering and exiting a battery during a specific interval to establish how much charge has been consumed. Although Coulomb Counting has been shown theoretically to be a very sound method of SOC estimation, the earlier studies also demonstrated poor accuracy due to the cumulative effect of measurement errors. The inexpensive current sensors create both a measurement offset and random white noise which will cause the estimated SOC after several integrations to significantly deviate from the actual SOC [10].

Also, there is significant literature evidence that Coulomb Counting depends on a precise initial state of charge in order to function correctly - this initial state of charge is almost never known in practice [14]. Many researchers are now using the Open Circuit Voltage (OCV) method to recalibrate the SOC (State of Charge) of the battery because of the deterministic relationship that exists between the OCV and SOC of the battery [8]. However, it has been established in the literature that the open-circuit voltage method is not a viable means of calibrating SOC's in many fast-moving applications, such as electric vehicles, because the batteries must be allowed to rest for long periods of time in order to achieve electrochemical equilibrium before they exhibit an accurate open circuit voltage (this can take several hours) [8, 10].

Given the inherent limitations associated with the various direct measurement methods, the research community has shifted significantly toward the use of model-based estimation methodologies [3, 4]. At this point, the majority of the literature is focused on the development of Equivalent Circuit Models (ECM) and Electrochemical Models (ECM). The Electrochemical Models (ECM) use mathematical and physical principles to replicate the electrochemical phenomena occurring inside the cell on a microscopic level (such as ion diffusion and the Butler-Volmer Equation, etc.). The literature has established that Electrochemical Models provide unmatched levels of accuracy; however, the need to solve coupled Partial Differential Equations makes real time embedded systems impossible to implement [14].

Consequently, many researchers have begun exploring the use of Equivalent Circuit Models as a means of characterizing battery performance through traditional electrical components such as resistors and capacitors [5].

Recent studies have put an increasing emphasis on deep learning, particularly with RNN and LSTM networks [11, 16]. Current literature indicates that LSTMs possess the ability to capture time-series information about battery deterioration and hysteresis by leveraging a distinct memory structure [11]. The data-driven methods investigated throughout the literature have been shown to provide increased accuracy for estimating SOC across the lifespan of a battery without any knowledge of the electrochemical processes involved [14, 17]. Conversely, the literature highlights the numerous barriers to commercialization, including high expectations of large amounts of highly diverse training data, the unpredictability of neural network performance outside the training dataset, and the exceedingly high computational resources required to implement deep learning models in real-time [10, 14].

To narrow the gap in theoretical versus practical accuracy, some of the most recent literature is primarily focused on hybrid approaches [14, 18]. Researchers are trying to create new ways to estimate SOC/SOH by creating hybrid estimation methods that marry the model-based filter and machine learning approach. For example, one such method provides real-time input into the parameters of a Kalman filter through use of an artificial neural network [12, 19, 20].

4 RESEARCH GAPS

- Most of today's highly accurate algorithms, like Particle Filter and Deep Neural Networks, require significantly greater computational power than what can be offered by most of today's low-cost Battery Management System (BMS) microcontrollers.
- Most of today's algorithms that provide estimates of SOC/SOH for batteries still have gaps, which do not allow for simultaneous and independent location of SOC/SOH without impacting each other negatively.
- Most current proposed estimation models lose significant accuracy in very low temperatures (below freezing) or very high temperatures, and have no robust thermal-coupled model.
- Current algorithm development techniques have only been validated in stationary, controlled environments, and they do not provide for the disorganized, high-frequency noise component that is found in real working conditions.

5. CONCLUSION

Accurate assessment of a lithium-ion battery's state of charge (SOC) is critical to the safe, reliable and efficient operations of the lithium-ion battery. This review explains that there is no single SOC estimation method that outperforms all others in every situation. Traditional SOC estimation methods, such as coulomb counting and voltage measurement, are easy to implement and require very little computational effort. However, they tend to be inaccurate over time due to the accumulation of error and the impact of changes in environmental conditions. Model-based methods are generally more accurate than traditional methods, can provide real-time data, but require an accurate model of the SOC estimation system in order to be successful. Data-driven and ML approaches are very powerful tools for capturing the complex and non-linear dynamics of the lithium-ion battery, especially in cases of varying conditions. However, these approaches require large quantities of data and are typically difficult to understand the underlying reasons for their results.

6. FUTURE SCOPE

After extensive review we have come up with a plan to develop hybrid methods by combining traditional methods with Machine learning and Deep learning. This will help to achieve highest accuracy and eliminating each method disadvantages. Apart from this a real time monitoring system will make a proper experimental support to the claims.

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