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Overview of State Estimation Methods and Research Progress of Power Lithium Batteries for Electric Vehicles

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Abstract: This paper presents a comprehensive research framework for state estimation of power lithium batteries by summarizing both model-based and non-model-based approaches. It provides an in-depth analysis of various methods, supported by experimental results. In the first part, the paper surveys model-based state estimation techniques, including the ECM (Equivalent Circuit Model), electrochemical models, and data-driven models. It systematically explains the principles behind these models and their respective applications. Additionally, the study delves into model-independent state estimation, emphasizing the utilization of machine learning algorithms in battery state estimation and the advancements in artificial intelligence technology. The potential of hybrid methods and intelligent algorithms in state estimation is also explored, highlighting possible future directions. The findings indicate that while model-based methods can attain high estimation accuracy in specific scenarios, they are constrained by model complexity and parameter uncertainty. The application of fusion method and intelligent algorithm further improves the performance of state estimation and provides strong support for real-time monitoring and prediction of power lithium batteries.

Keywords: Electric Vehicles; Power lithium battery; State estimation method.

1. Introduction

Amidst the escalating global energy crisis and environmental degradation, EVs (Electric Vehicles) have emerged as a promising, clean, and efficient transportation alternative, attracting significant attention and research [1]. The performance of the power lithium battery, being the heart of EVs, plays a pivotal role in determining their driving range, safety standards, and overall lifespan [2]. Therefore, accurately assessing the state of these batteries is paramount for enhancing EV performance, ensuring driving safety, and fostering sustainable growth within the EV industry [3].

In practical operations, however, power lithium batteries encounter various challenges, including fluctuations in charge-discharge rates, environmental temperatures, and battery aging, among others. These factors can induce changes in performance parameters, ultimately impacting battery state estimation [4]. Consequently, developing robust state estimation methods for power lithium batteries that can withstand complex working conditions has become a pressing and challenging research endeavor in the EV domain [5]. The objective of this study is to examine the efficacy of power lithium battery state estimation techniques and assess their practical performance.

2. Overview of EVs and Power Lithium Battery

2.1. EVs development overview and characteristics of power lithium batteries

EVs represent a significant advancement in transportation technology, offering zero emissions, reduced noise, and increased efficiency when compared to traditional fuel-powered vehicles [6]. As global energy crises and environmental pollution become increasingly urgent issues, EVs have garnered widespread attention and are actively being researched.

A crucial aspect of EV technology is the power lithium battery, which plays a pivotal role in determining the vehicle's range, safety, and longevity. These batteries exist in various types, including lithium-ion, nickel-hydrogen, and lead-acid, each distinguished by its electrolyte material and manufacturing process [7]. Lithium-ion batteries, in particular, stand out due to their high energy density, long lifespan, and excellent self-discharge characteristics, making them a popular choice for EVs. The key components of a lithium-ion battery are detailed in Table 1.

Table 1. List of main components of lithium ion battery

Component	Materials/compounds	Main function
Positive pole	Lithium compound	Storage and release of lithium ions determine the energy density of the battery.
Negative pole	Carbon material	Store and release lithium ions, and cooperate with the positive electrode to generate current.
Electrolytic	Organic solvent+lithium salt	Responsible for the transmission of lithium ions between the positive and negative electrodes, which affects the charging and discharging performance of the battery.
Lack of mutual understanding	Polyolefin material	Isolate the positive and negative electrodes to prevent short circuit of the battery and ensure the safety of the battery.

Lithium-ion batteries boast a high energy density, enabling them to pack more electric power within the same weight or volume, thereby extending the driving range of EVs [8]. Moreover, these batteries exhibit a remarkable cycle life, enduring thousands of charging and discharging cycles without significant performance degradation. Additionally, lithium-ion batteries have a low self-discharge rate, allowing them to retain a substantial charge even after prolonged periods of inactivity. Nevertheless, these batteries also present some drawbacks, including elevated costs and extended charging durations.

2.2. Application of power lithium battery in EVs

In EV designs, power lithium batteries are often combined in various configurations - either series or parallel - to satisfy diverse voltage and capacity needs [9]. To guarantee the battery pack's safety and reliability, it is crucial to incorporate a battery management system. This system oversees essential battery pack parameters like voltage, current, and temperature, executing necessary control and safeguarding measures to ensure safe operation and extend the battery pack's lifespan. Furthermore, when designing and developing EVs, it's vital to consider the integration of the power lithium battery with other critical components like the motor and controller. Optimal performance of EVs is only achieved when these components seamlessly collaborate.

3. Basic Method of State Estimation for Power Lithium Battery

3.1. Definition and importance of battery state estimation

Battery state estimation involves the continuous and precise monitoring as well as forecasting of power lithium batteries' present condition. This encompasses assessing crucial metrics such as SOC (State of Charge), SOH (State of Health), SOP (State of Power), and SOS (State of Safety) [10]. These metrics directly correlate to the battery's performance, remaining capacity, degradation level, and potential hazards, all of which are pivotal for ensuring EV reliability, optimizing energy usage, and mitigating battery-related risks. By obtaining real-time battery data, damage from improper practices like overcharging or overdischarging can be minimized, extending the battery's lifespan. Furthermore, leveraging this information allows for refined vehicle energy management, enhancing efficiency, range, and overall user satisfaction with EVs.

3.2. Common battery state estimation methods

(1) Voltage-based Approach

The voltage-based approach is among the earliest techniques for assessing the state of power lithium batteries. It involves determining the battery's SOC and other state information by measuring its terminal voltage [11]. While there's a correlation between the terminal voltage and SOC during battery charging and discharging, factors like internal resistance, temperature, and aging can significantly impact the accuracy of this method.

(2) Current-based Technique

The current-based method estimates battery states, such as SOC, by gauging its charging and discharging current. It typically combines the initial SOC with current integration to calculate the current SOC. Unlike the voltage-based method, this technique is less affected by internal resistance and other factors, offering higher estimation accuracy. However, it relies on precise current measurements and an accurate initial SOC value to avoid error accumulation.

(3) Internal Resistance-based Method

This method judges battery states, particularly SOH, by measuring its internal resistance. Since internal resistance correlates closely with battery capacity and aging, it can provide insights into the battery's condition. However, measuring internal resistance often requires specialized equipment and is sensitive to factors like temperature and measurement frequency, limiting its practical applications.

(4) Data Fusion-based Approach

The data fusion-based method is a more recent state estimation technique. It utilizes advanced algorithms to estimate and predict battery states by combining data from various sensors (e.g., voltage, current, temperature, internal resistance), historical data, model predictions, and other information sources. This approach leverages the strengths of multiple data sources to enhance estimation accuracy and robustness. It can also handle battery performance changes and uncertainties through online learning and adaptive adjustments. However, it demands significant computing resources and real-time performance due to the large amount of data and complex algorithm operations involved. Additionally, challenges arise in ensuring data synchronization and determining weight distributions during multi-source information fusion.

Figure 1 compares the advantages and disadvantages of these methods. In practical applications, it's essential to select or combine suitable state estimation methods based on specific needs and conditions to achieve optimal results.

4. Research Progress of State Estimation Methods for Power Lithium Batteries

4.1. Research progress of model-based state estimation

(1) ECM

The ECM, a widely utilized battery model, simulates a battery's electrical behavior by integrating circuit components, including resistance, capacitance, and inductance. This model adeptly selects components and determines their connectivity based on the battery's charging and discharging patterns. Consequently, it enables the simulation and prediction of crucial battery parameters, such as voltage, current, and internal resistance. In state estimation, the ECM, when paired with techniques like the Kalman filter and particle filter, offers insights into battery conditions like SOC and SOH. Its prevalence in recent years owes to advancements in model precision and computational capabilities. Despite its popularity, the ECM faces challenges, particularly in accurately obtaining model parameters and adequately representing the battery's internal chemical processes. To enhance its accuracy and versatility, researchers continually refine the ECM, incorporating dynamic parameter identification methods and accounting for battery aging effects on model parameters.

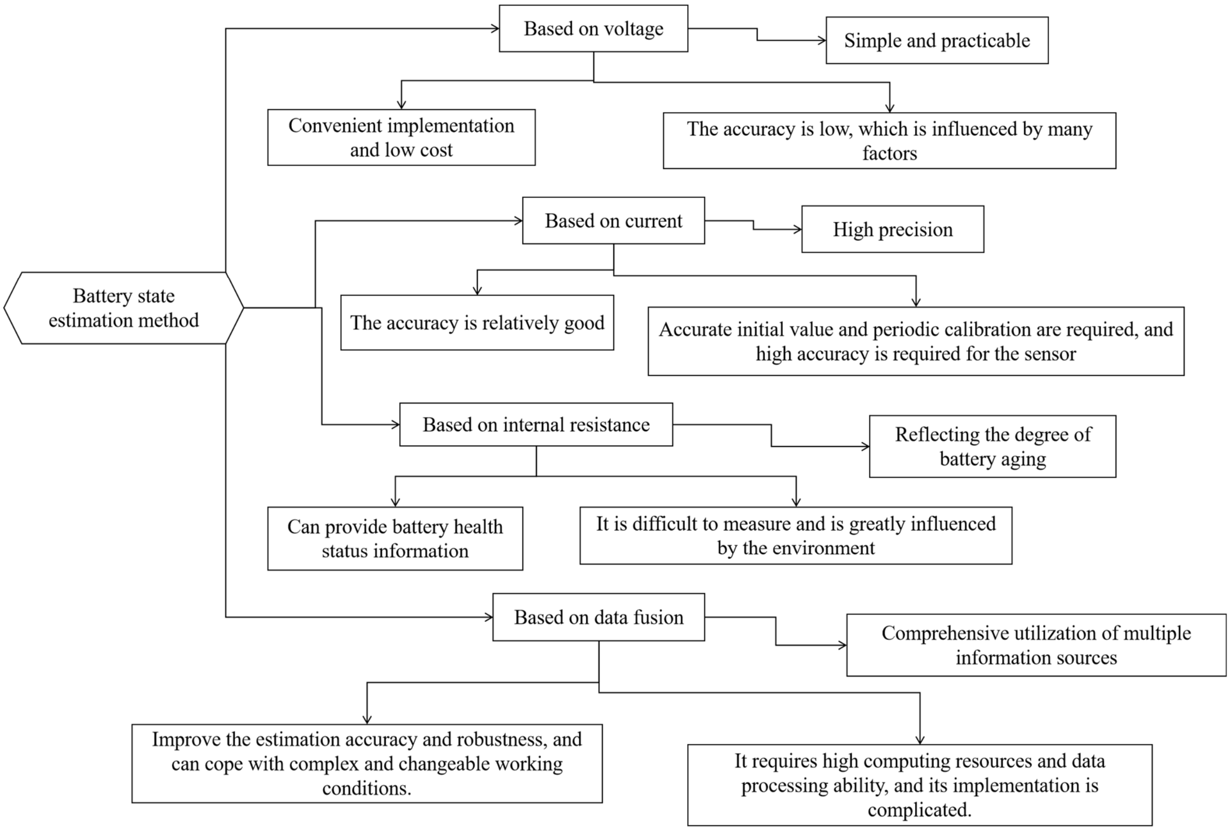

Figure 1. Comparison of advantages and disadvantages of battery state estimation methods

(2) Electrochemical Model

The electrochemical model is rooted in the battery's internal chemical reaction mechanisms. It simulates battery behavior by detailing the electrochemical interactions between its anode, cathode, electrolyte, and other components. This model provides a more nuanced understanding of the battery's internal states and operational principles, positioning it as a promising tool for battery state estimation. Its application, however, is hindered by its inherent complexity and computational demands, necessitating high-performance computing platforms and specialized electrochemical simulation software. Additionally, the numerous parameters within the model can be challenging to ascertain accurately, posing practical implementation difficulties. In recent years, researchers have addressed these challenges by simplifying the model's structure, optimizing computational methods, and exploring more efficient parameter identification techniques to bolster model accuracy.

(3) Data-driven model

The data-driven modeling approach constructs battery models using extensive experimental or historical datasets. Rather than relying on a deep comprehension of the battery's internal physicochemical processes, this method leverages data correlations to formulate the model and assess its state. Characterized by its simplicity and adaptability, the data-driven model has become a popular tool in battery state estimation. Typical examples of such models encompass neural networks, support vector machines, random forests, and other machine learning techniques. Through the analysis of vast datasets, these algorithms establish nonlinear relationships between battery states and input features, enabling precise state estimations. Recently, the emergence of deep learning has significantly advanced data-driven models based on deep neural networks, leading to notable progress in battery state estimation.

4.2. Research progress of model-independent state estimation methods

The model-independent approach for battery state estimation bypasses the need to model the intricate physical and chemical processes within the battery. Instead, it relies directly on measured data or relevant information to assess the battery's state, offering flexibility and broad applicability. This practical approach has garnered significant attention.

(1) Incorporating Machine Learning in Battery State Assessment

Machine learning, a data-driven technique, establishes relationships between battery states and input features through extensive data training. In battery state estimation, this method effectively tackles complex nonlinearities and uncertainties, enhancing the accuracy and resilience of assessments.

(2) Advancements in Artificial Intelligence for Battery State Determination

The evolving landscape of artificial intelligence has introduced numerous innovations to battery state estimation. Deep learning, for instance, can handle more sophisticated estimation challenges through its deep neural network structures. Meanwhile, reinforcement learning adapts to its environment to learn optimal estimation strategies, and transfer learning leverages prior knowledge to streamline the learning of new tasks. These AI advancements have opened up exciting new frontiers in battery state estimation.

4.3. Application of fusion method and intelligent algorithm in state estimation

The application of fusion method and intelligent algorithm in battery state estimation refers to the organic combination of multiple methods or algorithms to make full use of their respective advantages and improve the performance of state estimation. For example, the model-based method can be integrated with the data-driven method, and the accuracy and robustness of state estimation can be improved by using the model's ability to describe the physical and chemical processes inside the battery and the data-driven method's ability to deal with complex nonlinear problems. A variety of intelligent algorithms can also be integrated, such as combining neural network with particle filter to realize real-time and accurate estimation of battery state. The key problems to be solved in the application of fusion method and intelligent algorithm include how to choose appropriate fusion strategy and algorithm, how to optimize algorithm parameters to improve performance and so on. In order to solve these problems, researchers continue to explore new fusion methods and algorithms, and at the same time optimize and improve them according to the actual application requirements, so as to promote the further development of battery state estimation technology.

5. Challenges and Prospects of State Estimation for Power Lithium Batteries

Significant advancements have been made in estimating the state of power lithium batteries, yet practical challenges persist. Firstly, the intricate chemical reactions within batteries defy simple modeling, resulting in model inaccuracies and parameter uncertainties. Secondly, numerous factors — including temperature, aging, and charge/discharge rates—affect battery performance, making their precise simulation in real-world scenarios challenging. Lastly, acquiring and processing data, especially high-dimensional and time-varying data, poses significant challenges in effectively extracting features and denoising.

As science and technology evolve, along with computing power, battery state estimation techniques are trending towards enhanced precision, speed, and adaptability. There's a growing focus on data-driven and AI-based methods. These approaches leverage the strengths of big data and machine learning algorithms to extract valuable insights from vast datasets, bolstering estimation accuracy and robustness. Meanwhile, with the emergence of 5G, cloud computing, edge computing, and other technologies, the real-time and online learning capabilities of state estimation are poised for further enhancement. This promises even faster and more precise battery state monitoring and prediction.

6. Conclusions

In this paper, the basic methods, research progress, challenges and prospects of state estimation of power lithium batteries are systematically and deeply studied. In the aspect of model-based state estimation, the common methods such as ECM, electrochemical model and data-driven model are introduced, and their advantages and disadvantages and application scope are analyzed. In the realm of model-independent state estimation, the integration and advancement of machine learning algorithms and artificial intelligence in battery state assessment are deliberated. Furthermore, the potential utilization of combined methodologies and intelligent algorithms in state estimation is explored. Through comprehensive research and analysis, it is evident that accurately estimating the state of power lithium batteries poses a intricate yet pivotal challenge, necessitating a diverse array of methods and algorithms to bolster precision and resilience. Concurrently, as science and technology evolve and computational capabilities augment, state estimation techniques will undergo continuous refinement and expansion, thereby offering substantial impetus to the sustainable progress of the electric vehicle industry.

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