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Paul Takyi-Aninakwa, Shunli Wang,
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TABLE OF CONTENTS

FOREWORD

The development of new energy technology is crucial to address the world energy crisis and work towards achieving carbon neutrality. This book focuses on new energy technology centered on lithium-ion batteries. It explores concepts such as equivalent circuit modeling, parameter identification, and state estimation in lithium-ion battery power applications. The book provides a systematic description of key technologies in battery state estimation based on battery equivalent modeling and parameter identification methods of lithium-ion batteries. It covers an overview of lithium-ion batteries, equivalent modeling, state-of-charge estimation, and cycle life estimation, and emphasizes the significant impact of temperature on battery performance. Additionally, it offers practical references for the design and application of lithium-ion battery management systems, catering to the technical requirements of lithium-ion battery applications. The book stands out for its use of various methods and techniques for state estimation, along with rich examples that can serve as a guide and reference material. It can be used as a textbook for majors such as control science and engineering, automation, electrical engineering, and related fields in colleges and universities. Furthermore, it serves as a valuable resource for researchers and professionals in new energy measurement and control.

PREFACE

In recent years, power battery technology has evolved and advanced. Lithium-ion batteries have become the most common type of energy storage technology. The battery management system (BMS) checks the lithium-ion battery pack's operational status and controls the available energy during the energy storage and supply process. Because of the high safety standards and complex operating conditions of lithium-ion battery packs, equivalent circuit modeling and state of charge (SOC) estimation in BMS applications has become a hot research topic.

After years of developing high-power lithium-ion batteries' BMSs, the authors have compiled a book that focuses on the technical requirements and applications of high-power lithium-ion batteries in new energy vehicles. The book provides knowledge and expertise on lithium-ion battery equivalent modeling and state estimation, aiming to serve as a technical reference for the design, modeling, and application of lithium-ion BMSs. Additionally, the book offers recommendations for the global development of new energy technology and application industries.

This book was written and compiled by the new energy measurement and control research group at Southwest University of Science and Technology, among other collaborative institutions. The research team specializes in novel energy detection and control, and they have extensive teaching and research experience, as well as a long history of combining production, education, and research. The book is divided into five chapters and is based on research findings about relevant topics. Dr. Paul Takyi-Aninakwa created the overarching framework and oversaw its supplements, modifications, and finalization. Dr. Paul Takyi-Aninakwa is a postdoctoral researcher at the Southwest University of Science and Technology. He also supervises Master's degree students. The research team contributed to the book's content.

Professor Shunli Wang of Inner Mongolia University of Technology has thoroughly reviewed the entire book. Additionally, Professor Huang Qi from the Southwest University of Science and Technology has generously provided a wealth of reference materials for the book. Professor Yujie Wang from the University of Science and Technology of China has offered numerous constructive comments on the publication of the book. Lastly, our heartfelt thanks go to our colleagues for their invaluable contribution to this book's success. We are also grateful for and acknowledge the help and support of all other professionals and institutions who contributed to the scientific and technical know-how of this book.

The monitoring of lithium-ion battery conditions covers a wide range of areas but may be limited by the authors' level of knowledge. As a result, there may be some inaccuracies in the organization and compilation of the book. Readers are encouraged to provide constructive criticism and corrections via tapaul@swust.edu.cn and https://www.researchgate.net/profile/Paul-Takyi-Aninakwa. We hope that this book can facilitate the exchange of knowledge and help us connect with readers, ultimately contributing to the advancement of key technologies for monitoring the states of lithium-ion batteries.

1

INTRODUCTION

1.1 Research background

Conventional energy sources used in transportation, manufacturing processes, and electricity production are causing environmental pollution, including global warming. As a result, batteries have emerged as an alternative energy storage and power supply system to reduce these effects [1, 2]. A battery is an electrochemical device that can store electrical energy as chemical energy and then convert it back to electrical energy when needed. Batteries are known to be clean and efficient in energy storage systems. Various battery technologies have emerged since Alessandro Volta invented them in 1800 [3]. Rechargeable batteries, such as lithium-ion batteries, are gradually becoming the main power source and storage system [4]. They are preferred compared to batteries with other chemistries such as nickel-cadmium (NiCd), nickel-metal hydride (NiMH), and lead-acid ($PbSO_4$) due to their unique advantages [5]. These advantages include high energy density (about 250 Wh/L), high power density (12 kW/kg), low self-discharge rate (~5% per month), wide operating voltage (4.2–2.5V), wide operating temperatures, no memory effect, long cycle life (3000 cycles for capacity loss of 80%), lightweight, fast charging capability, good Coulombic efficiency, 95% recyclability after the end of life, etc. [6]. They have become the key to solving current energy problems and are widely used as power sources in electric vehicles (EVs), smart grids, aircraft, aerospace equipment, and many advanced technological devices [7]. Furthermore, the cost, thermal reactivity, difficulties in manufacturing, and greenhouse gas emissions during manufacturing and disposal are common negative points of this battery technology [8]. Therefore, to ensure the safe operation of the battery system and extend the working life of the battery, accurate estimation of battery status is of great significance [9].

As society continues to rapidly develop, serious problems such as global warming, greenhouse gas emissions, energy shortages, and air pollution are becoming more prevalent. These issues are causing significant difficulties for human health and life. Environmental protection and the development of clean energy have become common goals among countries worldwide [10]. Driven by the need for environmental protection and the construction of a better livelihood for humanity, the global energy structure is gradually shifting from traditional highly polluting fuels, such as fossil fuel and coal, to new, clean, and efficient energy sources. Furthermore, the prices of these fuels are rising at an exponential rate, necessitating the use of a secondary energy source for transportation [11]. Various nations have been actively promoting energy reform and striving to establish a new energy system that is pollution-free and environmentally friendly to address the global call for environmental protection and resolve the energy crisis. The "Energy Saving and New Energy Automobile Industry Development Plan" was issued by the State Council of China in 2012. The document outlined the government's commitment to promoting the development of the new energy automobile industry and integrating it into the national "863" major scientific and technological research projects in China. Also, investments in this industry are quite high, and it is expected that the global market demand for EVs will approach $1.2 trillion by 2027 [12]. Special scientific and technological projects, such as the promotion of new energy sources, smart grids, energy conservation, and emission reduction, have been included in national research topics. With the strong support of national policies, China's new energy industry has made breakthrough progress.

As environmental deterioration continues to worsen, EVs are being developed globally as a promising and strategic solution for sustainable fuel consumption and mitigating the environmental impacts related to the transportation sector [13]. The rise of electric vehicles (EVs) is evident from the consistent increase in their global sales over the years. In 2012, only 125000 EVs were sold worldwide, but this number has increased significantly to 6.75 million units in 2021. This trend signifies that EVs are gradually replacing conventional internal combustion engine vehicles, as their market share has increased from 0.2% to 8.3% within a decade [14]. Based on these trends, it is possible to imagine the future of road transport. There are various perspectives from which the emergence of EVs can be justified. There are four types of EVs: (1) hybrid electric vehicles (HEVs, 20–60 kW); (2) plug-in hybrid electric vehicles (PHEVs, 60–90 kW); (3) fully battery electric vehicles (BEVs, 80–100 kW); and (4) fuel cell electric vehicles (FCEVs). The widespread use of EVs has numerous benefits, including (1) reducing oil dependence and gas emissions; (2) decreasing the carbon footprint and promoting carbon neutrality; (3) leading a green transportation revolution; and (4) effectively battling climate change [15].

Depending on the source of electricity, the development of EVs on a global scale is recognized as one of the most efficient solutions [16, 17]. The State Council's article "New Energy Vehicle Industry Development (2021-2035)" states that in 2022, China's automobile industry will gradually enter the market with the guidance of national policies [18]. China's new energy vehicles are experiencing rapid development by proposing to achieve net-zero emissions by 2060, thanks to the introduction of relevant strategic policies [14]. As a result, the global sales of new energy vehicles have continued to rise. The lithium-ion batteries serve as the main power source of these vehicles and their installed capacity has seen a steady increase year by year [19]. The trend of power battery installed capacity in China over the past five years is shown in Figure 1-1.

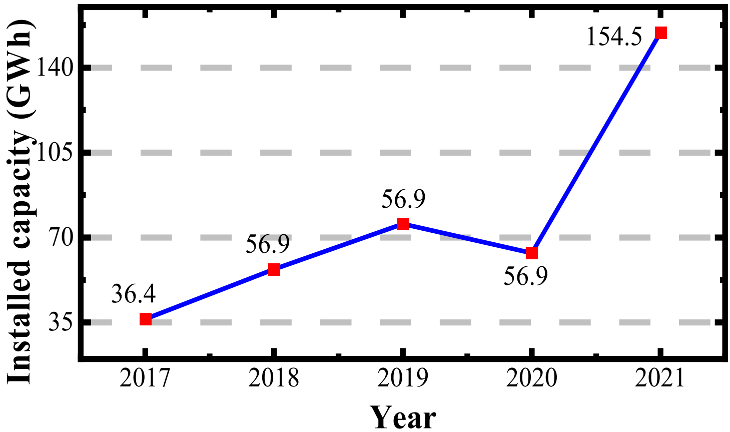


Figure 1-1. China's power battery installed capacity

One of the key functions of an energy storage system is to be a source of additional power when the main power source of the system cannot meet the power demands. Fuel cells [20], sodium-ion batteries [21], lithium-ion batteries [22], and other power battery types are currently among those with promising future development [23]. The new energy sector is rapidly developing and lithium-ion batteries are gaining attention for their unique advantages in energy storage, long lifespan, and eco-friendliness. They are extensively used as power sources in energy storage, aerospace, special robots, and more. To save on economic costs and ensure battery safety, scientists from different countries have conducted extensive research on battery efficiency improvement, lifespan extension, and status estimation [24].

1.2 Research significance

The battery management system (BMS) is an embedded electronic module responsible for maintaining the reliable and safe operation of batteries that are connected to deliver high currents at high voltage levels by monitoring working states, such as operating temperatures, discharge rates, and battery aging as well as the safety of users in practical applications [25, 26]. As an embedded electrical component in EVs, the BMS essentially functions to ensure cell monitoring, state estimations and modeling (including the state-of-charge (SOC), state of health (SOH), state of energy, state of power, etc.), fault diagnosis and health management, cell balancing, thermal management, charge-discharge control, etc. [27]. In addition, it does well in keeping the batteries under favorable conditions that allow them to fulfill their functional design requirements and make the best use of them [28].

Capacity, also known as coulombic capacity, refers to the total ampere-hour (Ah) of stored electrical energy that can be withdrawn from a fully charged battery under specific conditions. These conditions include discharge rate, temperature, aging level, and any discharge cutoff criteria specified by the battery manufacturer or user [29]. When a battery is fully charged, the remaining capacity (Ah) represents the total amount of electricity that can be used under defined working conditions. Accurate SOC estimation of lithium-ion batteries is highly dependent on the capacity status of the battery to ensure their safety and reliable operations, which is the function of the BMS [30, 31]. The SOC indicates the ratio of the remaining battery capacity to the maximum possible charge that can be stored in the battery. It ranges from 100% for a fully charged battery to 0% for a completely discharged battery [32]. The SOC, which is analogous to the fuel gauge in internal combustion engine vehicles, indicates the total energy remaining in the batteries of EVs and other smart devices that employ batteries as their source of energy [33]. On the other hand, the changes in the battery's resistance, maximum power, or discharge capacity are used to define the SOH [22, 34, 35].

As a critical state parameter of the battery, the SOC and SOH estimated by the BMS is of great significance due to the following reasons:

1) Accurate battery SOC and SOH estimations indicate battery remaining energy information to BMS, playing a crucial role in preventing unexpected system interruptions. In addition, due to the instability and flammability of the molten electrolyte, lithium-ion batteries can potentially ignite or even explode when overcharged, undercharged, or

over-discharged, resulting in permanent damage and a largely reduced battery life [36, 37]. The prevention of these issues can minimize the battery's aging rate and be of economic importance [38].

2) In applications like EVs and electromobility devices, accurately estimating the SOC can help users have enough information to calculate and plan the remaining driving range to eliminate driving anxiety issues based on remaining battery energy [39].

3) The SOC and SOH parameter estimations are crucial functions of the BMS. They serve as a foundation for optimizing power system energy, distributing power system energy rationally, and enhancing energy utilization efficiency. These are highly significant in reducing the economic cost of lithium-ion batteries, making them an essential aspect of overall energy management [40].

4) The SOC and SOH estimations are crucial factors for battery fault diagnoses, cell balancing, determining power state, and formulating discharge strategies. Besides, the incidents involving EV fires show that continuous battery operation without explicit consideration of SOC may cause thermal runaways or even explosions, which is one of the primary safety concerns for lithium-ion batteries [41, 42]. Thermal runaway is an irreversible state of the battery caused by an internal short circuit in the initial stage, resulting in an increase in local cell temperature and eventually combustion until the internal reactive materials are burned out. Thermal runaway is dangerous in industrial applications because it can cause an explosion in lithium-ion batteries. This is an irreversible and exothermic reaction in lithium-ion batteries that can cause fire, explosion, economic losses, and even mass mortality [43, 44].

5) Based on the literature review, it is crucial to maintain the battery under normal operating parameters, as the operating conditions have a direct impact on the aging process of the battery. Therefore, to extend the battery's life cycle, it is recommended to maintain the battery parameters such as temperature, current, SOC, and depth of discharge within the appropriate ranges while the battery is in use [40].

Without accurate SOC and SOH estimations or updates by the BMS, the user will experience an over or under-estimated range or less acceleration. To ensure the reliability and safety of EVs and their users, it is essential to monitor the battery's state parameters, which includes figuring out when the battery is getting close to the end of its useful life and how much power and energy it has remaining until that point [45, 46].

1.3 Battery SOC calculation

The state-of-charge (SOC) is a measure of the remaining capacity of an electric vehicle's (EV) battery to the maximum possible capacity (nominal capacity) that can be stored in the battery. The SOC is a critical factor that directly affects the driving range of an EV and also influences the other estimation functions of the BMS. However, in this research, battery tests are conducted at different current rates for both discharging and charging cycles. Therefore, the SOC calculation for both cycles can be expressed, as shown in Equation (1-1).

$$SOC_k = 1 - DOD_k = SOC_0 \pm \frac{1}{Q_n}\int_0^N \eta I_{L,k}\Delta t \tag{1-1}$$

In Equation (1-1), SOC_k and SOC_0 denote the current and initial SOC values, respectively, and η is the Coulombic efficiency, which is assumed to be 1. DOD_k is the depth of discharge value at time step k, where Coulombic efficiency and self-discharge are neglected. $I_{L,k}$ is the load current value at time step k, which is negative for charging and positive for discharging. Q_n is the current maximum available or nominal capacity, which may be different from the rated capacity due to the aging effect. N and Δt denote the number of data samples and the sampling time interval (0.1 second), respectively. $\pm$ denotes the addition and subtraction of the Ah integral method with reference to SOC_0 for the charging and discharging phases, respectively.

1.4 Research status

Several researchers have proposed a variety of SOC estimation methods. In combination, the main research methods include experimental or direct measurement methods, Ah integral method, battery model-based methods, and data-driven methods. In recent studies, hybrid estimation methods have been employed for state estimation of lithium-ion batteries by complementing the advantages of the individual estimation method to produce good results [47, 48].

1.4.1 Research status of SOC methods

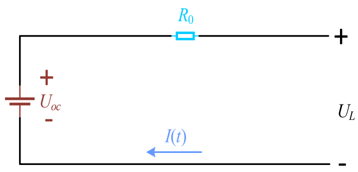
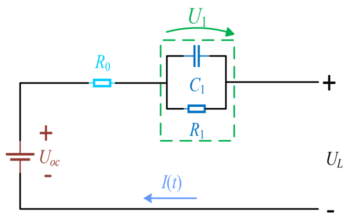
Several researchers have proposed a variety of SOC and SOH estimation methods. In combination, the main research methods include experimental or direct measurement methods, the ampere-hour (Ah) integral method, model-based methods, and data-driven methods [49, 50]. In recent studies, hybrid estimation methods have been employed for state estimation of lithium-ion batteries by complementing the advantages of the individual estimation method to produce good results [47, 48].

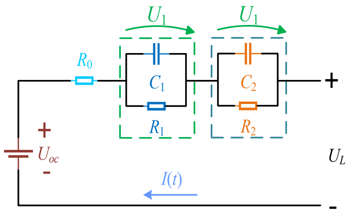
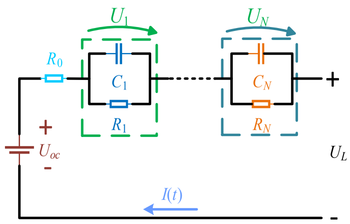
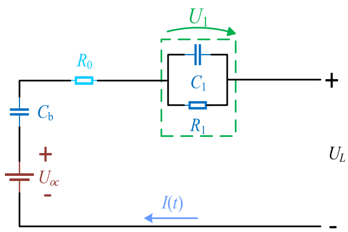
The experimental or direct measurement methods depend on the characterization of battery parameters, which include electrochemical impedance spectroscopy (EIS), the open-circuit voltage (OCV) method, and the internal resistance method, among others [51, 52]. The EIS measures the battery's impedance characteristics across a wide range of frequencies. While the implementation of EIS is straightforward, it requires complex computation and is highly dependent on the battery's state and external working conditions [53-55]. The OCV method can be used to estimate the SOC by mapping the relationship between the OCV and SOC values. This method is considered the most straightforward, as the electrochemical potential is closely related to the number of active materials still present in the electrodes. However, it is not suitable for EVs because it takes a long time for the battery to recover and measure the OCV value, which may cause false OCV measurements due to the internal capacitor reserving some electricity [56]. Whenever the battery's OCV-SOC relationship and measurement voltage are inaccurately measured and modeled, it results in inaccurate SOC estimation [57, 58]. Moreover, the accuracy of voltage measurement is highly dependent on the discharge characteristics of some batteries, which have a flat plateau and are difficult to obtain [59, 60]. Also, several experimental tests must be completed in advance to obtain the functional mapping relationship between relevant variables, which reduces the generalization of this method [61].

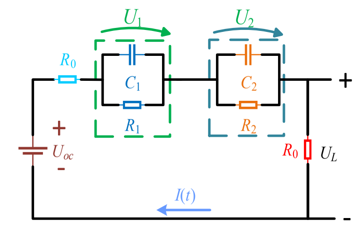
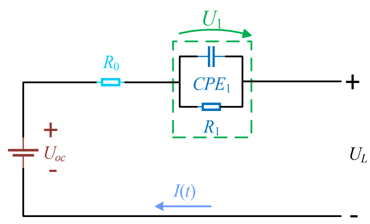
The Ah integral method is a simple and easy-to-implement technique for estimating SOC by integrating the current flowing to and from the battery [62]. This method, however, is heavily reliant on the initial SOC value and can be influenced by incorrect initial values and errors, coulombic efficiency, current sensor errors, and battery capacity that can cause the accumulation of errors during the integration process, leading to increased inaccuracies due to fluctuations in the load current [63-65]. In real-time applications, precise measurements of the load current are difficult, which can reduce the accuracy of the SOC estimation. Therefore, precise measurements of the load current and recalibration of the initial SOC are required, which can be challenging in real-time applications [66]. Second, the accuracy of this method is determined by the current and voltage sensors. However, the working conditions of lithium-ion batteries are complex, and sensors are often affected by uncontrollable factors, such as ambient temperature and noise, which can lower the data acquisition accuracy, leading to cumulative errors during the integration process [67]. Moreover, determining the coulombic efficiency under different working conditions can be challenging. Lastly, battery aging can cause energy attenuation, reducing the baseline energy value and resulting in decreased accuracy in SOC estimation [68].

The SOC and SOH can be estimated using the model-based method based on the battery model parameters established by the nonlinear state observer, which has become a research hotspot due to its simplicity, low computational complexity, real-time applicability, and robustness [69]. These state observers, with feedback correction capability, estimate the SOC or SOH by simplifying the battery as a dynamic system and presenting the state-space equation based on the established battery model. It treats the state of the battery as a hidden state and builds a state-space model that links it to measure battery variables, such as current and voltage [60]. Battery models commonly used for these methods to estimate the state parameter include the empirical model, electrochemical model, and electrical equivalent circuit model (EECM) to monitor and control the electrochemical states and equilibrium potential of the battery [70, 71]. Common EECMs, mainly the Thevenin EECM, high-order RC EECM, general non-linear (GNL) EECM, fractional-order EECM, etc., are compared and summarized, as shown in Table 1-1

Table 1-1. Comparison of commonly used EECMs for lithium-ion batteries

Model	Architecture	Electrical behavior	Advantages	Disadvantages
Internal resistance (Rint) EECM [72]		$U_L(t) = U_{oc}(t) - I(t)R_0$	• Simple structure; • Easy to implement; • Low computational cost	• Polarization phenomenon neglected during charging and discharging; • Low accuracy; • Poor dynamic performance; • Variable parameters are defined as constants;
Thevenin EECM [73]		$U_L(t) = U_{oc}(t) - U_1(t) - I(t)R_0$	• Simple and intuitive structure; • Low computational complexity; • Excellent applicability and expansibility;	• Low model accuracy in low SOC levels; • Incapable of estimating battery operational states;

Second-order RC EECM [74]		$U_L(t) = U_{oc}(t) - U_1(t) - U_2(t) - I(t)R_0$	• Slightly small estimation error; • Better trade-off between estimation difficulty and accuracy;	• High computational time than the Thevenin model;
High-order RC EECM [75]		$U_L(t) = U_{oc}(t) - U_1(t) -, \dots, U_N(t) - I(t)R_0$	• High simulation accuracy	• The amount of calculation is large and the physical meaning is unclear.
PNGV EECM [76]		$U_L(t) = U_{oc}(t) - U_0(t) - U_1(t) - I(t)R_0$	• High model accuracy; • Electrochemistry effects considered; • Excellent dynamic characteristics;	Incapable of describing low-frequency impedance characteristics; • Charging process neglected;

GNL EECM [77]		$U_L(t) = U_{oc}(t) - U_0(t) - U_1(t) - U_2(t) - I(t)R_0$	• High model accuracy; • Clearer physical meaning of component; • Influence of over-discharge and over-charge considered;	• Time-consuming calculation; • Complex structure; • Not suitable for practical engineering application;
Fractional-order EECM [78]		$U_L(t) = U_{oc}(t) - CPE_1(t) - I(t)R_0$	• High simulation accuracy;	• High computational cost in identifying the different parameters of the battery;

Note: R_0: Internal ohmic resistance; R_1: Electrochemical polarization resistance; R_2: Concentration polarization resistance; C_1: Electrochemical polarization capacitance; C_2 : Concentration polarization capacitance; U_{oc}: Open-circuit voltage U_1 : Electrochemical polarization voltage; U_2: Concentration polarization voltage; R_s: Self-discharging resistance; CPE: Constant phase element;

Compared with electrochemical models and mechanistic models, EECMs are currently in widespread use and have the benefits of having a clear physical meaning, simple mathematical expression, and less computational cost [79]. A battery model, mostly an EECM, is established for the state observer to characterize the dynamic parameters, which largely determine the accuracy. The EECM monitors and simulates the dynamic characteristics of the battery by using electrical components, such as resistors, capacitors, and constant voltage sources, to form circuit networks [73]. For example, ohmic internal resistance is used to simulate the battery's ohmic resistance, and one or more resistor-capacitor (RC) parallel circuit networks are used to simulate the battery's electrochemical and concentration polarization impedance effects based on kinetic voltage behavior [80]. This method employs EECMs to equate the battery with a mathematically described circuit model before selecting an observer or filter for state estimation. The EECMs do not take into account the electrochemical properties of batteries or the corresponding electrochemical reactions, instead relying on electrical components as a trade-off between accuracy and computational cost, making them the preferred choice for SOC estimation of lithium-ion batteries [81]. Currently, model-based methods include state observers, such as the auto-recursive Kalman filter (KF) [82], extended Kalman filter (EKF) [83], unscented Kalman filter (UKF) [84], particle filter [85], H-infinity filter [86], sliding mode observer, and their optimized variants, which have proven to estimate appreciable results [87-90]. These methods are sufficiently robust against inaccurate SOC initialization and measurement noise [91]. However, it has been discovered that their performance is largely dependent on the accuracy of the underlying battery model [92]. When the battery is subjected to complex load profiles and adverse working conditions, modeling the voltage behavior becomes extremely difficult. As a result, the state observer battery model is frequently subjected to model parameter identification by trial and error, resulting in poor SOC estimation and increased computation [93, 94]. Other downsides of this method include significant calculation sensitivity and difficulties under demanding operating conditions, such as high current, low temperature, low charged state, etc., affecting the accuracy of the battery models [95-97]. Therefore, this results in a laborious parameter-tuning process, which can cause unreliable SOC estimations [98]. Furthermore, it necessitates a thorough examination of the battery's electrochemical processes, which necessitates time-consuming and complex computations [99-102].

Due to technological advancement in recent years, there has been much research on emerging technologies, such as artificial intelligence, big data, cloud storage, and cloud computing. Data-driven methods have been significantly utilized because of their excellent self-adaptation, self-learning, and high estimation accuracy of the state parameter [103]. When it comes to these methods, the battery is considered a "black box" model rather than a practical mathematical model [104]. This estimation method is model-free, and its performance depends on the quality of the data, with proper training and hyperparameter selection being crucial [105, 106]. This model makes use of feature extraction and adequate training and testing datasets to directly map the nonlinear correlations between the state parameter and the measured variables, such as current, voltage, and temperature [107, 108]. It takes into account various nonlinear stresses such as the current rate, cell aging, operating temperature variations, and other working conditions that affect the battery, which is difficult to establish for the model-based estimation methods [109, 110]. These methods have served as the most favorable method to overcome the limitations of other existing methods [111]. Furthermore, they accurately estimate SOC with a single set of model parameters, whereas other conventional methods require multiple models with varying parameters under different working states [112].

Several data-driven methods have been proposed for SOC and SOH estimation, which have shown promise in overcoming the limitations of existing methods [113]. Data-driven approaches have been employed for accurate SOC and SOH estimation of lithium-ion batteries due to their high estimation accuracy. Machine learning (ML) models, such as support vector machine [107], k-nearest neighbor [113], linear regression models [114], and Gaussian process regression [115] have been proposed for SOC estimation because of their simple estimation process and less computation. However, these models do not account for the battery's strong nonlinearities, such as electrochemical, electrothermal, and material deterioration characteristics under complicated operational conditions [116]. Moreover, the accuracy and performance of these models are largely dependent on the quality and amount of input data, and imbalanced datasets can lead to over-fitting and under-fitting issues [117]. On the other hand, deep learning (DL) models have gained significant interest in the literature on SOC estimation. DL models, such as deep feed-forward neural network (DFFNN), convolutional neural network (CNN), and other advanced recurrent neural networks (RNNs) such as long short-term memory (LSTM), gated recurrent unit (GRU) network, nonlinear autoregressive network with exogenous inputs (NARX), can automatically map nonlinear temporal correlations between battery data and its state parameter. These models may self-learn their weights and biases utilizing gradient descent methods without the need for mathematical models, eliminating the requirement for tedious parameter adjustment [118, 119]. However, estimating battery state parameters using data-driven approaches necessitates a large quantity of experimental data, resulting in high computing costs and the need for accurate sensors to acquire battery-related data. The effectiveness and efficiency of the methods or networks depend on the researcher's ability to make them practical and engineering-relevant [120, 121]. Therefore, the DL models' application is relevant to practical research and engineering and highly depends on the researcher's ability to make the method or network effective and efficient in achieving the research objective.

It is not possible to directly measure the state parameters of a battery due to the high nonlinearities caused by the battery materials and dynamic working conditions. These state parameters can only be estimated using verified estimation methods that rely on quantifiable battery parameters, such as current, voltage, and temperature [122]. Figure 1-2 compares the primary state estimation methods used, along with their respective advantages and disadvantages.

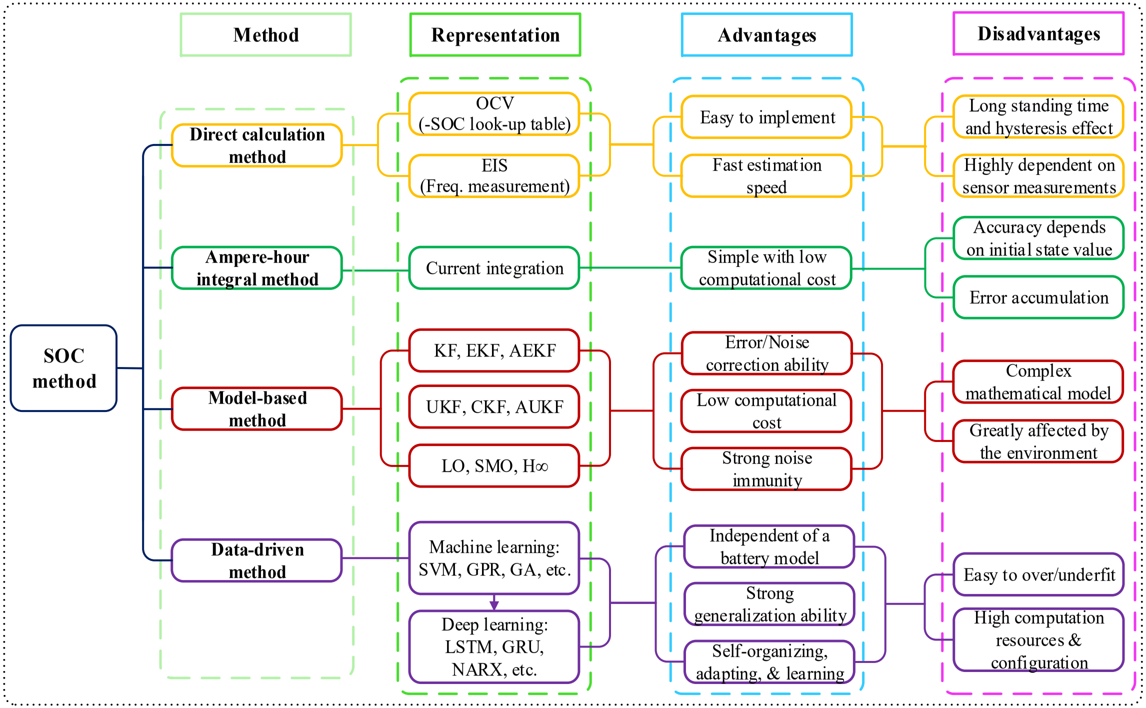


Figure 1-2. Categorization of SOC and SOH methods for lithium-ion batteries

Model-based SOC and SOH estimation methods have high accuracy while incurring moderate computation costs. Furthermore, data-driven methods have been shown to have excellent self-learning and adaptability capabilities when creating nonlinear mapping for complex nonlinear systems like lithium-ion batteries. As a result, the research presented in this dissertation employs a multi-fusion method based on a data-driven method and a canonical model-based method, combining their strengths to achieve accurate SOC and SOH estimation of lithium-ion batteries.

1.4.2 Research status review

Several methods based on DL have been proposed to overcome their limitations for estimating the SOC of lithium-ion batteries. They have been proposed by establishing a nonlinear connection between the measured variables, like current and voltage, and the output SOC. Gong et al. [123] developed a method known as CNN with an ultra-lightweight subspace attention mechanism and a simple recurrent unit to estimate SOC at room temperature. Chen et al. [124] proposed a method called denoising autoencoder (DAE) gated recurrent network to estimate the SOC under three different operating conditions. The DAE-NN is used to extract relevant features of battery data at room temperature. Ren et al. [125] presented a hybrid particle swarm optimization (PSO)-LSTM model to estimate SOC, which is compared with the LSTM at room temperature. This method is used for the estimation of SOC under noise characterization. Mao et al. [126] established an optimal backpropagation for SOC estimation of lithium-ion batteries and used a particle swarm optimization method with a levy flight strategy to optimize the weights and thresholds of the network. Jiao et al. [127] used a GRU-RNN to evaluate the efficacy of a momentum gradient technique and prevent weight change oscillation for SOC estimation speed improvement. They also looked at how momentum terms, noise variances, training epochs, and the number of hidden layer neurons affected the training speed and accuracy of SOC estimation. Chen et al. [128] developed an LSTM that maps nonlinear battery characteristics and reduces SOC fluctuations using sliding window average voltage data. Using conventional inputs, Tian et al. [129] developed an LSTM model with an adaptive cubature KF method that ensures accurate SOC estimation of lithium-ion batteries at temperatures ranging from 10 ℃ to 50 ℃ using conventional inputs. Yang et al. [130] devised a method for estimating SOC that uses LSTM-RNN to model complex battery behavior under different temperature conditions. At temperatures ranging from 10 to 50 °C, the estimated SOC is refined using a UKF to filter noise and minimize estimation errors. In addition, Fasahat et al. [131] and Chen et al. [124] investigated the use of a combinational method by serially connecting an autoencoder to the LSTM and the GRU, respectively. The autoencoder is used to extract useful data features from battery-measured variables, improving the RNN's ability to learn the battery nonlinear mapping rule. Despite efforts to tune the network hyperparameters, this problem persists, having a significant impact on both the stability and accuracy of the estimation, both of which need to be improved.

However, it is crucial to understand how different operating temperatures affect lithium-ion batteries to design the best thermal management systems that minimize thermal runaways during charging and discharging. To estimate the SOC of lithium-ion batteries, several temperature-based DL methods have been developed [132]. Ma et al. [116] co-estimated the SOC and state of energy using the LSTM model under two working conditions by utilizing different battery chemistry and noise interference datasets at temperatures of 0 °C, 10 °C, and 25 °C. At a temperature of 30 °C, Oyewole et al. [133] established a controlled deep transfer learning (CDTL) technique for short and long-term SOC estimation employing two LSTM models as source and target cells. Yang et al. [134] estimated the SOC using a GRU-RNN at temperatures ranging from 10 °C to 50 °C. Tian et al. [129] introduced an LSTM model with an adaptive cubature KF approach to provide accurate and resilient SOC estimations of lithium-ion batteries under dynamic loading profiles at temperatures ranging from 10 °C to 50 °C. Bian et al. [135] suggested a computationally complicated stacked bidirectional LSTM model for SOC estimate at 0, 10, and 25 °C under two working conditions. Yang et al. [130] established an LSTM-RNN to predict battery behavior at different temperatures to estimate the SOC of lithium-ion batteries. At temperatures ranging from 10 °C to 50 °C, the estimated SOC is paired with a UKF method to filter out noise and decrease estimation errors. Fasahat et al. [131] proposed a technique for estimating the SOC of lithium-ion batteries using an autoencoder neural network and an LSTM under two operating circumstances and temperatures of 0 °C, 25 °C, and 45 °C. Wang et al. [136] introduced an improved GRU-based transfer learning (TL) method for SOC estimation utilizing small target sample datasets at temperatures ranging from 32 °C to 50 °C under three working conditions. By refining the LSTM, Ma et al. [137] proposed a sequence-to-sequence mapping technique with a process information approach for SOC estimation. It enables modeling of state and process information with a two-stage pretraining technique adopted to improve the method's feature-learning capabilities at operating temperatures of 0 °C, 25 °C, and 45 °C.

It is important to understand how temperature affects SOC estimation of lithium-ion batteries when designing, training, and testing using the LSTM model. The United States Advanced Battery Consortium manual categorizes battery working temperatures for electric vehicles (EVs) into cold (T≤-8 ℃), cool (-8 ℃<T<0 ℃), normal (20 ℃±10 ℃), warm (30 ℃<T<38 ℃), and hot (T≥38 ℃) [138, 139]. Previous studies have not cross-trained and tested their methods under cold (-10 ℃), normal (25 ℃), and hot (50 ℃) temperatures to specifically study the effects of different training and testing temperatures on the SOC estimation accuracy under different complex working conditions. Instead, they estimated the SOC under different temperatures (0 ℃–50 ℃) and working conditions without proposing a robust method for solving the estimation effects.

On the other hand, one of the main obstacles to the data-driven SOC estimation methods discussed above is the difficulty in obtaining readily available features. Data-driven methods use machine learning mechanisms to estimate battery SOC without detailed electrochemical knowledge [140]. A few studies [141, 142] have explored statistical methods for selecting battery domain knowledge based on a few output parameters of the battery model to enhance SOC accuracy. However, these features are restricted to predetermined voltage responses and their significant variations. For instance, a method for developing a physics-informed deep neural network has been successfully developed by Tian et al. [141]. This method utilizes an LSTM and a KF-based approach to estimate the SOC using 10-minute charging current and voltage sequences. Another study [142] has also been conducted, which augments current and voltage sequences with OCV, ohmic voltage, and polarization voltage as inputs into the LSTM. Monitoring batteries is a complex and challenging task, as their electrochemical nature is highly intricate and exhibits nonlinear behavior under various internal and external operating conditions [143]. Considering these studies on battery state estimation, they fail to consider the inherent coupling relationship between battery states, such as the ohmic resistance, electrochemical polarization impedances, and concentration polarization impedances, which represent the intrinsic electric characteristics of the battery [144]. Furthermore, the accuracy and robustness of these methods must be improved while mitigating errors caused by full-cyclic current rates and temperature irregularities on the SOC.

1.6 Chapter Summary

In this chapter, the research background and status of the various SOC methods have been studied. As a crucial lithium-ion battery state parameter, the SOC cannot be measured but can be estimated using accurate and robust methods. Therefore, several methods have been proposed, including direct measurement methods, ampere-hour integral methods, model-based methods, data-driven methods, and hybrid estimation methods. The hybrid estimation methods are established based on the combination of the previously mentioned methods by combining the advantages of these methods to offer better accuracy and stability under various operating conditions. In order to verify these methods, the standard AME, MAE, RMSE, and R^2 are employed to investigate the actual performance of the various methods. In this way, it can be ascertained that the proposed method can perform in real-time BMS applications for EVs.