Frontiers in Power and Energy Systems (2025) DOI: 10.23977/fpes.2025.040107
Clausius Scientific Press, Canada ISSN 2516-2926 Vol. 4 Num. 1

A Review of Battery Aging Mechanisms and Health Status Estimation Methods under Wide Temperature Range

Jiarong Ni

Jiangsu Ocean University, Yangzhou, Jiangsu, China
2446759430@qq.com

Keywords: Lithium-Ion Battery; SOC Estimation; Temperature

Abstract: In the context of global energy transformation, the rapid development of new energy vehicles has put forward higher requirements, for the accuracy of lithium-ion battery state estimation. Ambient temperature changes will significantly affect the activity of internal battery materials and electrochemical reactions, resulting in increased errors in battery health status and state of charge estimation, threatening system safety. This paper reviews the attenuation mechanism of temperature in lithium-ion batteries, including electrolyte decomposition and SEI film thickening at high temperatures, lithium precipitation and interface degradation at low temperatures, and systematically analyzes the state of charge estimation methods based on model-driven (equivalent circuit, electrothermal coupling model) and data-driven (neural network, filtering algorithm). The research provides a theoretical reference for improving the adaptability of battery management systems in complex temperature environments.

1. Introduction

As the global energy crisis and ecological pollution problems intensify, the transformation and upgrading of the traditional energy industry system has become a global strategic issue. The power battery system based on electrochemical energy storage technology has promoted the rapid development of the new energy vehicle industry due to its clean and efficient characteristics and has gradually become an important technical path to replace fossil fuel transportation vehicles. The popularization of new energy vehicles can not only effectively alleviate the pressure of oil resource shortages, but also greatly reduce the harm caused by noise to the human body. In order to promote the development of the new energy industry and promote the transformation of transportation energy, the Chinese government has introduced a series of policies to support the research and development of new energy vehicle technology, clearly deploy and plan for the leapfrog development of China's automobile industry and provide opportunities for the promotion of electric vehicles and their power battery technology. [1]

At present, lithium-ion batteries are widely used in the production of new energy vehicles. As the core component of new energy vehicles and energy storage systems, the accuracy of their state estimation directly affects the safety and efficiency of the system. In the actual working environment, lithium-ion power batteries will be affected by many factors, which may reduce the accuracy of battery state estimation and increase the error. Among them, the working environment temperature will not only affect the material activity and charge and discharge performance of lithium-ion batteries, but also the maximum available capacity of lithium-ion batteries will change accordingly after temperature changes. In addition, the state of charge (SOC) and state of health (SOH) of lithium-ion batteries are nonlinear functions of ambient temperature. All of the above will lead to a decrease in the accuracy of battery state estimation and an increase in error, which seriously affects the durability of new energy vehicles and even causes the battery management system (BMS) algorithm to not converge, increasing the safety risks in vehicle use. [2] For example, the non-uniformity of the temperature gradient inside the lithium-ion battery affects the inconsistency of the electrochemical reaction rate, resulting in a decrease in the accuracy of SOC estimation; the fluctuation of the charge and discharge rate under dynamic conditions and the coupling of mechanical vibration cause the hysteresis effect of the open circuit voltage (OCV) and the interference of SOH evaluation. Therefore, real-time online estimation of the operating temperature of lithium-ion power batteries is particularly important.

Traditional battery temperature monitoring is based on thermocouples on the surface of lithium-ion batteries. The instantaneous change rate of ambient temperature is low, and the accuracy is not high. With the increasing demand for lithium batteries, many studies have been conducted on temperature estimation of lithium batteries at home and abroad. Fan Wenjie et al.[3] summarized a variety of methods for estimating the temperature of lithium-ion batteries. CHEN Lunguo et al.[4] used the charging and discharging experiments of lithium iron phosphate batteries at different temperatures to simplify the variable parameter thermal model and identify the equivalent internal resistance and thermal parameters, combined with the extended Kalman filter algorithm to achieve the estimation of the internal temperature of the lithium battery. Huang Tengfei [5] established a set parameter two-state thermal model of lithium-ion batteries, coupled the thermal model with the temperature-related second-order RC equivalent circuit model, and forms an electrothermal model of lithium-ion batteries. The temperature of lithium batteries is estimated using the Kalman filter adaptive calculation method. Sun Yongkuan[6] established a multi-parameter time-varying electric thermal coupling model (MPET) for batteries. The current was input into the electrical model to obtain open circuit voltage, terminal voltage and SOC. The calculation results of the electrical model were then input into the heat generation model to obtain the heat generation and heat transfer of the battery to calculate the internal and surface temperature of the battery. WANGY et al.[7] established a thermal-electric coupling model based on the dynamic internal resistance model (DIRM) to study the heat generation characteristics of battery cells and the thermal management temperature distribution, which can achieve accurate prediction of the operating temperature of lithium batteries.

So far, the bottlenecks that restrict the development of battery technology are mainly the following three aspects: (1) During the charging and discharging process, the battery exhibits highly nonlinear characteristics due to internal chemical reactions, heat and charge transfer processes, etc., which makes it difficult to accurately model it. (2)The internal state of the battery cannot be obtained by direct measurement methods, and is easily affected by ambient temperature, which reduces the accuracy of the internal state estimation of the battery. (3)The inconsistency of the battery pack directly affects the efficiency of the battery pack, resulting in battery performance and safety hazards.[8] Based on the existing literature, this paper collects and organizes the current domestic and foreign research results on the relationship between temperature and lithium-ion battery state estimation, as well as the results of lithium-ion battery temperature estimation research, and describes it from the analysis of the two driving methods of model and data and the existing SOH estimation method.

2. The influence mechanism of ambient temperature on lithium-ion battery aging

Ambient temperature has a significant impact on the working stability and cycle life of lithium-ion batteries, mainly manifested in high temperature accelerated aging and low temperature induced damage. At the same time, the internal volume expansion of the battery caused by changes in ambient temperature will also aggravate the aging of the battery. Yan Yukun[9] showed that the optimal working ambient temperature range for lithium-ion batteries is between 15 and 35 ℃. Under low temperature conditions, the reduced conductivity of the electrolyte leads to a decrease in the lithium ion transfer rate, which reduces the material utilization rate during the charging and discharging process, further leading to a decrease in the available capacity of the lithium-ion battery. When working in a high temperature environment, the internal side reactions of the battery are accelerated, resulting in the accelerated oxidation and decomposition of the electrolyte and the formation and thickening of the SEI film [10], which is intuitively manifested as capacity loss and increased impedance.

2.1 Attenuation mechanism of battery aging under high temperature environment

2.1.1 Oxidative decomposition of electrolyte

The discharge process of lithium-ion batteries is often accompanied by varying degrees of gas expansion, of which electrolyte oxidation and decomposition are the most important gas production reaction. There are two situations in which electrolyte decomposition occurs. One is that due to poor battery sealing, moisture in the air enters the soft-pack battery and comes into contact with the electrolyte, causing the electrolyte to decompose and produce gases such as CO2, H2, and O2; the other is that electrons pass through the SEI membrane and react with substances in the electrolyte to produce a large amount of hydrocarbon gas. [11]

Before lithium deposition, at a temperature above 40 ℃, the exposed lithium metal surface undergoes uncontrollable redox reactions with the organic electrolyte, such as solvent decomposition and $LiPF_6$ hydrolysis, to generate a mixed SEI film composed of Li_2O, LiF and organic lithium salt ($ROCO_2Li$). In addition, the side reactions continue to consume active lithium and degrade the electrolyte, while producing gas byproducts (CO_2, C_2H_4), increasing the interface porosity and forming a porous SEI layer.

Ethylene carbonate (EC) at high temperature to generate SEI components such as Li_2CO_3 and LiF, as shown in reaction formula (1); $LiPF_6$ has poor thermal stability and is easily hydrolyzed at high temperature. The HF generated at the same time will accelerate its hydrolysis reaction [12], as shown in reaction formula (2-3); HF generated by the hydrolysis of $LiPF_6$ reacts with Li_2O to form an inorganic salt LiF (lithium fluoride) crystalline layer deposition, which hinders the transport of lithium ions, as shown in reaction formula (4). The reaction of the organic lithium salt $ROCO_2Li$ is shown in reaction formula (5).

$$EC\ (C3H4O3)+2e\text{-}+2Li+\rightarrow Li2O+C2H4\uparrow+CO2\uparrow \tag{1}$$

$$LiPF6+H2O\rightarrow LiF+POF3+2HF \tag{2}$$

$$2HF+2Li^{+}+2e^{-}\rightarrow 2LiF+H_2\uparrow \tag{3}$$

$$Li2O+2HF\rightarrow 2LiF+H2O \tag{4}$$

$$EC+2e^{-}+2Li^{+}\rightarrow CH_2OCO_2Li(ROCO2Li)+Li_2CO_3 \tag{5}$$

2.1.2 Uncontrollable thickening of solid electrolyte interphase (SEI)

In addition to the known reversible volume change caused by the insertion and removal of lithium ions in the negative electrode graphite , lithium-ion batteries also undergo irreversible expansion, which causes the battery thickness to increase continuously. During the first charge and discharge process of lithium-ion batteries, the surface of the graphite electrode material is prone to irreversible reaction with the electrolyte to form a solid electrolyte membrane SEI, and the SEI membrane slowly grows with the increase in the number of cycles, which is the key reason for battery aging and thickness increase.(Figure 1)

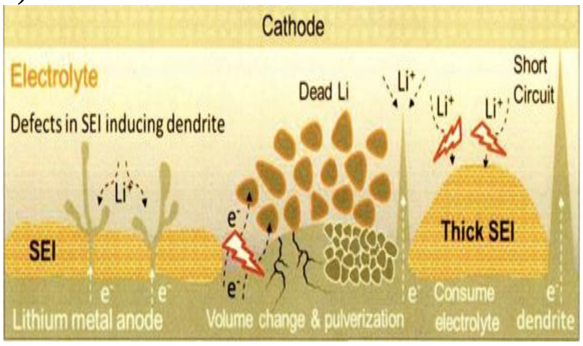


Figure 1 Principle of uncontrollable thickening of SEI film [13]

During the deposition process, the lack of constraints from the intercalation matrix will lead to a huge volume expansion during the deposition of lithium metal, which will cause the SEI film to mechanically rupture and expose the fresh lithium surface. In addition, due to the uneven and non-dense structure and composition of the original SEI film, the desolvated lithium ions will preferentially deposit at locations with high electronic and ionic conductivity, which will show synaptic growth and form lithium dendrites. The lithium dendrites will continue to grow and thicken on the original dendrites and form new dendrites. Some dendrites will break due to the release of internal stress to form "dead lithium", and some residual dendrites will penetrate the diaphragm causing micro short circuits. During the discharge process, the deintercalated lithium ions will generate a large number of pits and holes on the surface of the lithium metal electrode and leave a broken original SEI. The subsequent deposited lithium metal reacts with the electrolyte to form a composite inorganic/organic SEI thick layer. Its high impedance characteristics aggravate polarization, forming a heterogeneous deposition mode of "dead zone-active zone" alternation[13] . At this point, a large amount of active lithium is consumed. The loss of active lithium leads to a decrease in available capacity. The principle of SEI film thickening is shown in Figure 1. Liu Tong[14] selected four single lithium iron phosphate batteries and selected 15A to fully charge them in constant and current constant voltage (CCCV) mode and then discharged them at a constant current to a battery discharge cut-off voltage of 2.5V.

2.2 Impact of low temperature environment on battery health status

There are three main mechanisms for the impact of the low temperature environment on the state of health (SOH) of lithium-ion batteries: (1) capacity decay dominated by irreversible lithium deposition; (2) degradation of electrolyte ion transport performance; (3) triple coupling effect of interface stability destruction. At low temperatures (<0 ℃), the kinetic barrier for lithium ion embedding into the graphite negative electrode increases, causing some lithium ions to be directly reduced to metallic lithium on the negative electrode surface (lithium deposition reaction), forming dendritic or mossy deposits; at the same time, low temperatures cause the electrolyte viscosity to surge, causing concentration polarization to intensify, further amplifying the risk of lithium deposition. In addition, the solid electrolyte interface (SEI) is prone to mechanical rupture due to increasing brittleness at low temperatures, and the exposed fresh lithium surface continues to react with the electrolyte to form a thick and uneven composite SEI, resulting in a surge in interface impedance and blockage of lithium-ion transmission channels.

3. Health status estimation method under wide temperature range

Battery state of health (SOH) is usually used to characterize the degree of battery aging and is specifically defined as the ratio of the maximum charge capacity available in the current cycle to the rated capacity of the battery when it leaves the factory, as shown in formula (6) [15] .

$$SOH(C) = \frac{Q(C)_{MAX}}{Q_N} \tag{6}$$

Among them, $Q(C)_{MAX}$ represents the maximum charge capacity available in the current cycle, and Q_N represents the rated capacity of the battery when it is produced . At present, there are three main methods for estimating SOH : model-driven method, data-driven method and test analysis method, and their detailed classification is shown in Figure 2. Among them, the test analysis method directly obtains the characteristic parameters of the battery for SOH estimation, the model-driven method estimates SOH based on the battery model combined with filters and sliding mode observers, and the data-driven method obtains battery aging information and establishes a model based on experience and existing databases and combines advanced intelligent algorithms to realize battery SOH evaluation .

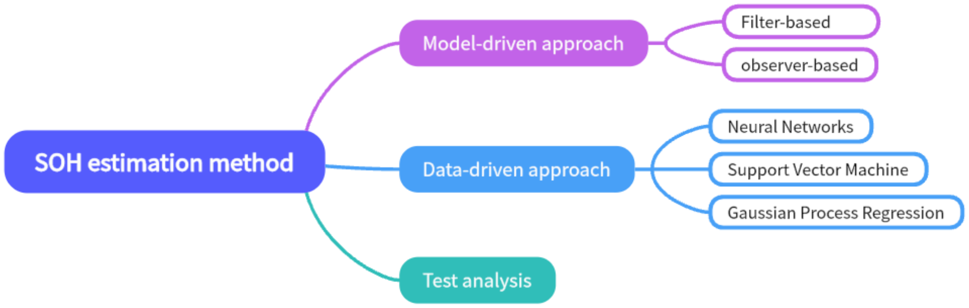


Figure 2 Classification of SOC estimation methods

3.1 Model-driven approach

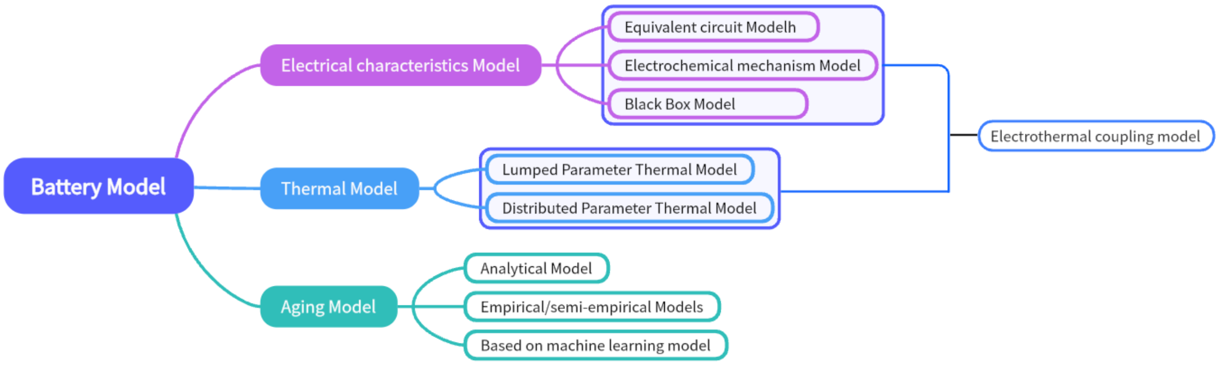


Figure 3 Detailed classification of battery models

The model-driven approach estimates SOH based on the battery model combined with filters and sliding mode observers , and battery modeling is a necessary prerequisite for estimating battery SOH. At present, lithium-ion battery models mainly include electrical characteristic models, thermal models, electrothermal coupling models, and aging models[16], as shown in Figure 3. The model-based approach mainly combines the battery model with other methods. Currently, the most studied and widely used method is the method that combines the battery model with filters or observers. This chapter summarizes the current equivalent circuit model, electrothermal coupling model, and SOH estimation under various filtering algorithms.

3.1.1 Equivalent circuit model

The equivalent circuit model is a circuit composed of resistors, capacitors, voltage sources, inductors and other circuit elements used to analyze physical parameters and characterize battery characteristics. Equivalent circuit models can be divided into two categories: integral order model [17] and fractional order model [18].

Common integral-order equivalent circuit models include the Rint model, Thevenin model, the PNGV model, second-order RC model, and multi-order RC model.[19] The initial integral-order model is the Rint model [19] , which is a resistor-inductor model consisting of only a voltage source and a resistor. The model has a simple structure and easy-to-determine parameters. Its basic principle is to estimate the inductance and internal resistance by the rate of change of the battery voltage during the charge and discharge process, thereby estimating the battery's state of charge. Although accuracy is not high, it lays the foundation for establishing a high-order model. The Thevenin model (first-order RC model), PNGV model, and second-order RC model are all gradually optimized for the Rint model. Specifically, the Thevenin model is based on the Rint model and adds an RC network. The RC network is used to simulate transient characteristic factors such as filtering, delay, integration, and differentiation in the circuit, and can reflect the polarization effect and internal resistance characteristics of the internal resistance; the PNGV model is based on the Thevenin model and a capacitor C is connected in series to describe the non-ideal characteristics and dynamic response of the battery; the second-order RC model continues to add an RC network to the Thevenin model, and further improves the accuracy of SOC estimation through the steady-state response and transient state response of the RC network.[20] Figure 4 shows the accuracy iteration process of the integral order model.

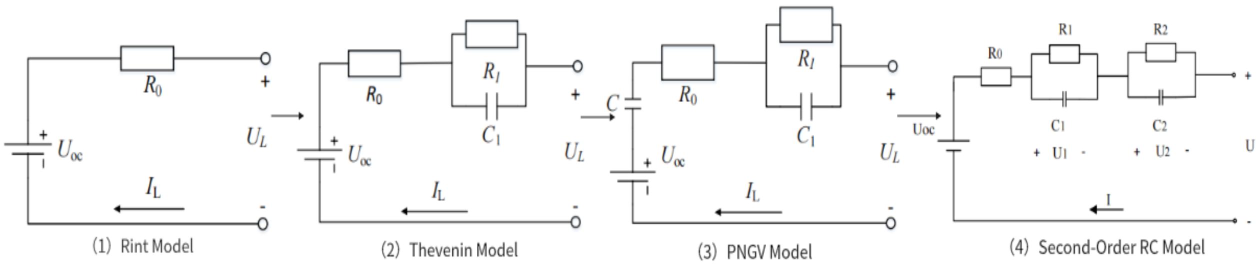
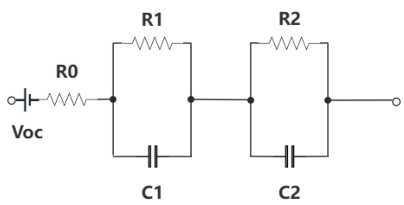
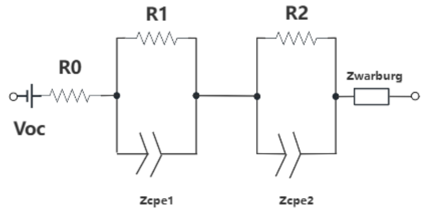


Figure 4 Iterative process of the integral order model

In recent years, fractional-order models have been proposed one after another. Their advantage is that they use constant phase elements (CPE) to replace the capacitors in the RC circuit to better simulate the charge transfer inside the battery in a wide frequency domain.[21] The advantages and disadvantages of integral order and fractional order are compared in Table 1. VOC is the open circuit voltage, R0 is the ohmic internal resistance, R1 and R2 are the polarization resistances, C1 and C2 are the polarization capacitances, ZCPE1 and ZCPE2 are the impedances of the two CPEs respectively, and ZWarburg represents the Warburg impedance.

Table 1 Advantages and disadvantages of different equivalent circuit models. [22] h

Model	Equivalent circuit model of integral order	Fractional Order Equivalent Circuit Model
Structure		
Advantages	The model is simple, easy to recognize and compute.	Applicable across all frequency ranges, providing a better simulation of battery physical phenomena.
Disadvantages	It is impossible to simulate the battery characteristics across the entire frequency range, and the extrapolation method is unreliable.	The structure is complex, and the computation is slow.

The most widely used equivalent circuit model is the second-order RC model, which was first proposed by Yann Liaw et al.[21] at the Idaho National Laboratory in the United States based on the first-order RC model. The state space equation of the second-order RC equivalent circuit model considering temperature changes is as follows:

$$\begin{cases} \dot{U}_1 = -\dfrac{U_1}{R_1 C_1} + \dfrac{I}{C_1} \\ \dot{U}_2 = -\dfrac{U_2}{R_2 C_2} + \dfrac{I}{C_2} \\ U_t = OCV - IR_0 - U_1 - U_2 \end{cases} \tag{7}$$

In the formula, R0 is the ohmic internal resistance; R1 and R2 are the polarization internal resistances; C1 and C2 are the polarization capacitances, U1 and U2 are the voltages corresponding to R1 and R2 respectively, and the polarization phenomenon of lithium ions is described by ohms, polarization resistance and polarization capacitance.

Gu Kangwei[20] used a second-order RC model to obtain the SOC-OCV curve through the static voltage method and then identifies the model parameters through the pulse discharge method. The sixth-order polynomial is used to achieve a fitting accuracy of 0.995. It is found that the mean absolute error (MAE), mean relative error (MRE) and root mean square error (RMSE) of the model at 6 different temperatures all decrease with the increasing temperature. At the same time, He Yeliang[23] compared different battery equivalent circuit models, and finally uses a second-order RC equivalent circuit model to identify the parameters of R and C in the circuit at 6 different temperatures, which also verifies the high accuracy of the second-order RC model.

In order to further verify the accuracy of the second-order RC model, Zhang Qichang[26] conducted a reverse verification. This literature introduced the concept of electrochemical impedance spectroscopy (EIS) to measure the composition of the equivalent circuit model. By measuring the EIS curves of the ternary lithium battery at different temperatures and fitting the obtained impedance data, the equivalent circuit model LR(RC)(R(CW)) model which is most suitable for the ternary lithium battery is obtained. In actual use, the equivalent circuit model is simplified, and the L and W components can be omitted. The circuit model of the final model is R(RC)(RC), that is, the second-order equivalent circuit model.

3.1.2 Electrothermal coupling model

In early studies, thermal models and electrochemical models were usually treated separately. The electrochemical model focused on electrical parameters such as voltage, current, and capacity based on electrochemistry, while the thermal model focused on the internal temperature distribution and heat dissipation of the battery based on lumped parameter models or distributed parameter models. The effects of temperature on electrochemical reaction rate, internal resistance, capacity attenuation, etc. were not considered, and the dynamic feedback of electrochemical heat generation on temperature distribution was not quantified. Therefore, the electrochemical-thermal coupling model came into being.

The electrothermal coupling model uses a mechanism model to describe the electrical characteristics of the battery, so its accuracy is higher than that of the general lumped parameter model, but the complexity is increased. Therefore, in order to improve the adaptability of the battery characteristic model to the ambient temperature and the limitations of sensor equipment in collecting the internal temperature of the battery, Wang Xindong.et al.[27] analyzed the heat generation, heat transfer and heat dissipation behavior of lithium-ion batteries, and establishes an electrothermal coupling model and parameter identification by combining the second-order RC equivalent circuit model with temperature changes and the two-state lumped parameter thermal model. This literature identifies the thermal physical parameters under a variable temperature environment by the recursive least squares method and proves the good accuracy of the established electrothermal coupling model. The two-state lumped parameter thermal model in the literature is established based on the heat generation and transfer process of the battery. The discretization expression of its second-order RC equivalent circuit model and the state space equation of the two-state lumped parameter thermal model are shown in Table 2.

Table 2 Related equations of sub-models of electrothermal coupling model

<table>
<tr><th>Model</th><th>State Space Equation</th><th>Discrete expressions</th></tr>
<tr><td>Second-order RC model</td><td>$\dot{U}_1 = -\frac{U_1}{R_1C_1} + \frac{I}{C_1}$
$\dot{U}_2 = -\frac{U_2}{R_2C_2} + \frac{I}{C_2}$
$U_t = OCV - IR_0 - U_1 - U_2$</td><td>$U_1(k) = \exp\left(-\frac{t}{R_1C_1}\right)U_1(k-1) + I(k)R_1\left[1 - \exp\left(-\frac{t}{R_1C_1}\right)\right]$
$U_2(k) = \exp\left(-\frac{t}{R_2C_2}\right)U_2(k-1) + I(k)R_2\left[1 - \exp\left(-\frac{t}{R_2C_2}\right)\right]$
$SOC(k) = SOC(k-1) + \eta\frac{I(k)\Delta t}{Q_n}$</td></tr>
<tr><td>Bimodal Aggregate</td><td colspan="2" rowspan="2">$C_C\frac{d(T_i - T_a)}{d_t} = q - \frac{T_i - T_a}{R_i}$
$C_s\frac{d(T_s - T_a)}{d_t} = \frac{T_i - T_a}{R_i} - \frac{T_s - T_a}{R_0}$</td></tr>
<tr><td>Total Heat Model</td></tr>
</table>

In the discrete expression of the second-order RC model, △t is the sampling interval; Qn is the maximum available capacity; SOC is the battery state of charge; η is the coulomb efficiency. In the state space equation of the two-state lumped parameter thermal model, Cc and Cs represent the equivalent heat capacity of the battery core and shell respectively; Ri and Ro represent the equivalent thermal resistance of the battery respectively, which are reciprocal to the heat transfer coefficient. Since the time-varying nature of the parameters of the sub-model of the electrothermal coupling model has a great influence on calculation accuracy, Sun Yongkuan further established a multi-parameter time-varying electric thermal coupling model (MPET)[6]. The model consists of a first-order RC equivalent circuit model and a four-state thermal model independently established by the author. It can quickly adjust the thermal physical parameters according to the changes in the external environment and input the heat generation rate into the heat transfer model to calculate the internal and external surface and core temperature of the battery at the next moment, effectively reducing the influence of the internal and external temperature of the battery on SOC estimation.

3.2 Data-driven approach

Commonly used data-driven SOH estimation methods include neural network (NN), support vector machine (SVM), Gaussian process regression (GPR), etc. The specific classification and their advantages and disadvantages are shown in Table 3.

Table 3 Comparison of data-driven methods [22]

	Category	Advantages	Disadvantages
NN	FNN	Good classification ability fast convergence speed	Algorithms don't work when data is insufficient
	BPNN	Can simulate and approximate any function	There may not always be a solution
	CNN	Strong expansion capability easy to train	No memory function
	LSTM-RNN	Long-term storage of information	Calculation time
	GRU-RNN	Small number of parameters, low risk of overfitting	Difficulty obtaining information from long ago
SVM		Good robustness	Large computing memory and long computing time
GPR		Performs well on nonlinear systems	Failure in high-dimensional space

3.2.1 Neural network model

The neural network model can perform black-box processing, feature extraction and learning on a large amount of input data through a multi-layer neural network structure. During the learning process,it continuously adjusts parameters, learns autonomously and has strong robustness. Therefore,the memory and learning capabilities of the neural network model are suitable for SOH estimation of lithium-ion batteries. Feedforward Neural Network (FNN) is the most common model in practice. It is a unidirectional model and each layer of neurons is a nonlinear function of the previous layer. In order to solve the problem of excessive errors in the data propagation process of each layer of neurons, an error back-propagation (BP) neural network was introduced. Since the traditional BP algorithm is a local search algorithm of gradient descent,Kong Deyang et al.[24] used genetic algorithm (GA) to improve the BP neural network, and uses the GA-BP neural network to accurately predict SOH based on the mean absolute error (MAE) and mean square error (MSE) as indicators . Recurrent Neural Network (RNN) is a type of neural network with short-term memory and a loop structure. In order to overcome the problem of gradient explosion or gradient diffusion of RNN, the structure of the original recurrent neural network is improved by redesigning the memory unit . A Long Short-term Memory Recurrent Neural Network (LSTM) is proposed. Lin Hao [25] used LSTM with current, voltage, and temperature as the time input data of the input layer. The simulation results show that the prediction accuracy of this model for SOH is better than other models. However, due to the large number of internal unit gates of the LSTM model, the gradient vanishing problem still occurs when there is a lot of data. In order to solve the problem of reducing the gradient vanishing while retaining long-term sequence information, a gated recurrent unit recurrent neural network

(GRU) is introduced. The GRU neural network model is used to estimate the SOH, which can add the estimation time and reduce hardware consumption [26].

3.2.2 Support Vector Machine Method

Support vector machine (SVM) is a new type of learning machine based on statistical learning theory. Compared with NN, it can improve the generalization ability of machine learning[27] and is often used to solve problems such as small samples, high dimensions and local minima [28]. Wang Yuyuan et al.[29] used the Least Squares Support Vector Machine (LSSVM) model based on SVM, and compared the estimation with SVM using the root mean square error RMSE and determination coefficient R2 as evaluation criteria. It is found that the LSSVM estimation value is more consistent with the SOH value. Zhang Yue[30] proposed an SOH estimation based on the Gray Wolf Optimized Support Vector Machine (GWO-SVM) algorithm, which optimizes the penalty parameter C and the width coefficient of the Gaussian kernel function. The overall estimation error is lower than SVM error, which effectively improves the accuracy and robustness of the battery state. Compared with SVM , the Relevance Vector Machine (RVM) can express the uncertainty of the prediction results and reduce the calculation amount of the kernel function.

4. Summary and Outlook

As a core component of new energy vehicles, the accuracy of state estimation of lithium-ion batteries directly affects system safety and efficiency. However, changes in ambient temperature significantly affect battery performance, resulting in increased errors in state of charge (SOC) estimation. High temperatures can cause loss of active lithium and capacity decay; low temperatures can cause a surge in interface impedance and obstruction of lithium ion transmission. In view of the mechanism of temperature's influence on SOC, existing studies have proposed two types of estimation methods based on model-driven and data-driven. The model-driven method is based on the equivalent circuit model, simulates the battery polarization effect through the second-order RC model, combines the electrothermal coupling model to quantify the dynamic relationship between temperature and electrochemical parameters, and uses the Kalman filter algorithm to improve estimation accuracy. The data-driven method uses machine learning techniques such as neural networks (such as BP, LSTM) and support vector machines (SVM) to autonomously learn the nonlinear characteristics of the battery by inputting voltage, current and temperature data. Comparative experiments show that the GRU model and adaptive filtering algorithms (such as ASTSCKF) have higher robustness and accuracy under variable temperature conditions. However, high model complexity, time-varying parameters and strong data dependence are still the current technical bottlenecks.

References

[1] Wang Dengyi. Research and development status and future prospects of new energy vehicles in China[J]. China New Communications, 2019, 21(17): 236.

[2] Luo Fan, Huang Haihong, Wang Haixin. Rapid prediction of state of charge and health status of retired power batteries based on electrochemical impedance spectroscopy[J]. Chinese Journal of Scientific Instrument, 2021, 42(09): 172-180.

[3] Fan Wenjie, Xu Guanghao, Yu Boning, et al. Research on online estimation method of internal temperature of lithium-ion batteries based on electrochemical impedance spectroscopy[J]. Proceedings of the CSEE, 2021, 41(09): 3283-3293.

[4] CHEN Lunguo, HU Minghui, CAO Kaibin, et al. Core temperature estimation based on electro-thermal model of lithium-ion batteries[J]. International Journal of Energy, 2020

[5] Huang Tengfei. State estimation and charging management of ternary lithium-ion batteries based on electro-thermal-mechanical coupling characteristics[D]. Jilin University, 2024.

[6] Sun Yongkuan. Analysis of coupled heat dissipation characteristics of power batteries and optimization of thermal management strategies considering SOH[D]. East China Jiaotong University, 2024.
[7] Wangy, Tianj, Sunz, et al. A comprehensive review of attery modeling and state estimation approaches for advanced battery management systems [J]. Renewable and Sustainable Energy Reviews, 2020, 131: 110015.
[8] Yang N, Zhang X, Shang B, Li G. Unbalanced discharging and aging due to temperature differences among the cells in a lithium-ion battery pack with parallel combination. Journal of Power Sources. 2016;306:733-741
[9] Yan Yukun. Automotive power battery degradation analysis and health status assessment[D]. Jilin University , 2024.
[10] Liang Haobin, Du Jianhua, Hao Xin, et al. Research status of the expansion formation mechanism of lithium batteries[J]. Energy Storage Science and Technology, 2021, 10(02): 647-657.
[11] Cao Xiaoyan, Li Ling, Wang Jia, et al. Study on the hydrolysis behavior of LiPF6[J]. Journal of Ocean University of China (Natural Science Edition), 2005,(06):148-150.
[12] Gan Lu. Construction and deposition behavior regulation of artificial SEI of lithium metal anode[D]. Zhejiang University, 2023.
[13] Huang Yusha. State of charge and health estimation of lithium-ion power batteries[D]. University of Science and Technology of China, 2022.
[14] Liu Tong. Research on numerical calculation and test method of electrochemical-mechanical coupling model of lithium iron phosphate battery[D]. Beijing Jiaotong University, 2022.
[15] Peng Ziran, Wang Shunhao, Xiao Shenping, et al. A cycle gating model for accurate estimation of SOC & SOH of electric vehicle power batteries[J]. Journal of Electronic Measurement and Instrumentation, 2024, 38(09): 11-23.
[16] HU Xiaosong,TANG Xiaolin.Review of modeling techniques for lithium-ion traction batteries in electric vehicles Journal of Mechanical Engineering,2017,53(16):20-31
[17] JOHNSON V H.Battery performance models in ADVISOR [J].Journal of Power Sources, 2002, 110(2): 321-329.
[18] XUJ,MICC,CAOB,etal.A new method to estimate the imstate of charpedance modelge of lithium-ion batteries based on the batter [J].JournalofPowerSources,2013,233:277-284
[19] Aung H, Low KS,Goh S T. State-of-charge estimation of Lithium-ion battery using square root spherical unscented Kalman filter (Sqrt-UKFST) in nanosatellite [J]. IEEE Transactions on Power Electronics, 2015, 30(9): 4774-4783.
[20] Gu Kangwei. Lithium battery SOC estimation considering temperature influence[D]. Nanjing University of Posts and Telecommunications, 2023.
[21] Freeborntj, Maundyb,Elwakilas. Fractional order models of super capacitors, batteriesand fuel cells: Asurvey [J].Materials for Renewable and Sustainable Energy,2015,4(3):1-7.
[22] Zhao Xuan, Li Meiying, Yu Qiang, et al. A review of state estimation of lithium batteries for electric vehicles[J]. China Journal of Highway and Transport, 2023, 36(06):254-283.
[23] He Yeliang. Research on SOC estimation of lithium battery considering temperature influence [D]. Anhui University of Science and Technology, 2021.
[24] Kong Deyang, Ding Chenyang, Liu Jiaxin, et al. Prediction of real vehicle battery health at all times based on back propagation neural network improved by genetic algorithm [J/OL]. Journal of Tongji University (Natural Science Edition), 1-10 [2025-05-17].
[25] Lin Hao. Research on SOC and SOH estimation of lithium-ion batteries based on neural network [D]. Guangdong Polytechnic Normal University, 2024.
[26] Zhang Qichang. Research on SOC and SOH estimation algorithm for lithium-ion power batteries [D]. Nanjing University of Aeronautics and Astronautics, 2019.
[27] Wang Xindong, Dong Zheng, Wang Shuhua, et al. SOC estimation of lithium-ion batteries under wide temperature and multi-operating conditions based on improved open circuit voltage model and adaptive square root unscented Kalman filter[J]. Transactions of the Chinese Society of Electrotechnical Engineering, 2024, 39(24): 7950-7964.
[28] Wang Wen. Research on power battery health status assessment algorithm [D]. Qingdao University of Science and Technology, 2020.
[29] Wang Yuyuan, Li Jiabo, Zhang Fu. Battery state estimation based on least squares support vector machine with particle swarm optimization[J]. Energy Storage Science and Technology, 2020, 9(04): 1153-1158.
[30] Zhang Yue. Research on online joint estimation method of lithium power battery state based on GWO-SVM algorithm[D]. Harbin University of Science and Technology, 2023.