Research on capacity degradation and aging state estimation of lithium-ion battery

Xu Li, Qi Zhang, Bowen Yang, Dafang Wang*, Shengmin Cui
School of Automotive Engineering, Harbin Institute of Technology, Weihai, Shandong, 264209, China
*Corresponding author’s e-mail: wangdf@hit.edu.cn

Abstract. The aging state estimation of the power battery is very important for the battery management system (BMS). Regular estimation of the battery’s state of health (SOH) can improve the service life of electric vehicles. The reasons for the aging of lithium-ion battery are briefly introduced in this paper. What’s more, the estimation methods of battery aging state are summarized and described from both the model-based and data-driven aspects.

1. Introduction
Recently, the share of electric vehicles in the automotive market has seen explosive growth. The increase in the number of electric vehicles has put forward higher requirements for the cycle life and reliability of power batteries. However, capacity degradation is inevitable. Some external factors such as extreme temperature and abnormal charging and discharging conditions can accelerate battery aging and even cause battery failure. Capacity degradation of the battery will not only reduce the car's cruising range, but also affect the accuracy of state of charge (SOC) estimated by BMS. The battery may be in a state of overcharging and overdischarging, causing more serious failures. Therefore, it is of great significance to estimate SOH of the battery regularly. It can not only improve battery performance and battery life, but also effectively avoid safety problems caused by battery aging failure.

2. Reasons for lithium-ion battery aging

2.1 Internal reasons
Internal reasons mainly include loss of lithium inventory (LLI), conductivity loss (CL) and loss of active material (LAM). Available lithium ions mainly come from the cathode material. When the battery is working, lithium ions are intercalated back and forth between the positive and negative electrodes, and the stability of the positive and negative electrode structures decreases or even collapses. As a result, not all lithium ions can be inserted back into the structures, resulting in the loss of lithium ions. The formation, destruction and regeneration of solid electrolyte interphase (SEI) can also lead to the loss of lithium ions. CL is mainly due to the aging of electronic components, such as the corrosion of the collector. LAM usually related to the dissolution and consumption of the positive and negative active materials of the battery and the loss of electrolyte[1-2].

2.2 External reasons
Different external factors will affect the internal reaction process of the battery, such as ambient temperature, charge and discharge rate and charge method (overcharge and overdischarge), etc.
Charging and discharging at too low a temperature will cause lithium deposition reaction in the battery, which will seriously damage the health of the battery. When charging and discharging at a high rate for a long time, the interface polarization of the electrode and electrolyte and the reaction polarization of the active material will increase significantly, making the battery impedance also increases. The charge-discharge cut-off voltage will also cause irreversible attenuation of the battery capacity. Too high or too low cut-off voltage will damage electrode structures of the battery, making it impossible to insert lithium ions back into the electrode fully, causing lithium deposition, and even cause safety hazards such as short circuits.

3. Estimation of battery aging state

3.1 Model-based estimation method
There are currently different classification standards for model-based battery aging state estimation research, such as equivalent circuit model (ECM), electrochemical mechanism-based model (EMM), and hybrid model.

3.1.1 Equivalent circuit model
The ECM does not consider the internal chemical reaction process and mechanism of the battery, only uses electronic components such as resistors and capacitors to build the model based on the electrical characteristics. The common ones are Rint model, Thevenin model, PNGV model and more complex models improved based on the above models[3], as shown in Fig.1. Qian K et al. used a second-order RC equivalent circuit to describe the voltage relaxation, and obtained characteristic parameters that can distinguish ohmic polarization, reaction polarization, and concentration polarization by simulating the voltage relaxation curve, and used parameter sensitive changes to evaluate battery aging state[4]. Fang L L et al. used the forgetting factor recursive least squares method to identify model parameters on the basis of the ECM, and proposed a joint estimation method. Double extended Kalman filter algorithm is used to analyse the battery SOC-OCV curve, battery capacity and parameters by building an error estimation model, through which SOC and SOH are jointly estimated[5].

3.1.2 Electrochemical mechanism-based model
The EMM describes the microscopic physical and chemical reaction process based on the complex electrochemical phenomenon and aging mechanism inside the battery, and can characterize the essence of the battery, but the modeling process is quite complicated. A. Lamorgese et al. simulated a simple lithium-ion battery aging model based on electrochemical thermally coupled pseudo-two-dimensional (P2D) theory, and estimated capacity attenuation by evaluating the loss of recyclable lithium ions at each time point[6]. Yang S C et al. coupled the EMM with the thermodynamic model to study the battery degradation and aging. The model describes the anode side reaction and the loss of cathode active materials, and studied the battery aging behavior under different discharge rates and ambient temperatures[7].
3.1.3 Hybrid model
Hybrid model generally refers to the model based on the ECM combined with the battery chemistry mechanism to improve the accuracy of the model. An electrochemical-equivalent circuit unified parameter model based on the electrochemical mechanism and ECM is established to study the side reactions of the battery negative electrode, and established the battery aging model through the side reaction control equation to study the aging of the battery. Typical aging values such as the internal resistance, growth of the deposition layer and SEI film and are used to characterize the aging state[8].

3.2 Data-driven estimation method
This method mainly focuses on the estimation algorithm or parameters which can characterize battery aging. A large amount of data are used for training to make the model result consistent with the measured data, instead of studying the battery itself. Current, voltage, capacity, impedance, and temperature, etc are collected to estimate SOH with the help of algorithms. There is no need considering the internal electrochemical reaction and aging mechanism of the battery, let alone the establishment of a complex electrochemical system model, so it has gradually become a research hotspot in recent years.

3.2.1 SOH estimation based on machine learning algorithm
Common algorithms include artificial neural network (ANN), support vector machines (SVM), relevance vector machine (RVM), fuzzy algorithm (FA), gaussian process regression (PGR), etc. Shehzar Shahzad Sheikh et al. proposed a method to study battery health and state of charge, using machine learning algorithms to extract important features from the discharge curve to estimate SOH and SOC, mainly relying on powerful learning algorithms to achieve state estimation[9]. T-S fuzzy control is used to establish a dynamic prediction model. With the number of cycles, voltage drop and internal resistance change as the input, and the corresponding SOH weight as the output, the SOH is calculated according to the SOH weight and boundary conditions[10]. The wavelet denoising (WD) method is also combined with the PGR to predict the remaining battery life[11].

3.2.2 SOH estimation based on filtering algorithm
Filter-based estimation algorithms usually include two steps: prediction and correction. A state equation is supposed to be constructed, which takes the parameters (internal resistance, capacity, etc.) representing SOH as state variables to establish a state space model, to realize dynamic tracking and prediction of running conditions. Then the filtering algorithm is used to solve SOH iteratively[12]. Commonly used filtering algorithms include particle filter (PF), Kalman Filter (KF), extended Kalman Filter (EKF), unscented Kalman Filter (UKF) and so on. Chen Z P established an 18650 battery state of health estimation model, proposing an improved battery SOH estimation method based on the UKF algorithm[13].

3.2.3 SOH estimation based on time series algorithm
This method is based on past trends to predict future development. Simple sequence average method, weighted sequence average method, moving average method, and weighted moving average method are commonly used. These methods assign different weights according to the degree to which the data affects the predicted value at different times in the moving segment, and then use the average value to predict the future value. Auto-regressive moving average model (ARMA), long short-term memory (LSTM) and recurrent neural network (RNN) are also important methods for time series forecasting[12]. Empirical mode decomposition (EMD) was used to separate the global deterioration trend and capacity regeneration from the health state time series, which were used in the ARIMA model to predict the global deterioration trend and capacity regeneration respectively[14]. Qu J T et al. proposed to combine LSTM networks with particle swarm optimization and attention mechanisms to estimate the RUL and SOH of lithium-ion batteries[15].
3.2.4 SOH estimation based on capacity increment curve

The capacity increment (IC) curve is derived from the battery voltage curve and represents the capacity change corresponding to the change in unit voltage. The voltage curve changes relatively smoothly, making it difficult to detect weak characteristics changes. The IC curve has multiple peaks and valleys, which can characterize the phase change reaction of the battery, and the peaks of the waves will move in height and position as the battery ages, as shown in Fig.2. The battery SOH can be estimated quantitatively combined with the regression algorithm. Weng C H et al. used IC analysis to identify reliable features related to battery aging to predict SOH[16]. Li X Y et al. used gray relational analysis (GRA) with entropy weight method to extract health indicators based on IC curve. The entropy weight method is used to evaluate the significance of each health index and SOH is evaluated by calculating the gray correlation degree between the reference sequence and the comparison sequence[17]. IC curve can also be combined with PGR to predict the health of the battery[18].

![Fig.2. The capacity increase curve changes with the number of battery cycles](image)

3.2.5 SOH estimation based on linear relationship between parameters and capacity decay

Some scholars predict aging state by looking for the linear relationship between certain variables and the battery SOH. There is no need to build a complex model and no need for powerful algorithms. For example, Tang X P et al. introduced the concepts of regional capacity and regional voltage to predict the SOH of four batteries based on the IC curve, finding that SOH and regional capacity present a simple linear relationship, which can directly predict SOH. This method is efficient and novel, insensitive to noise and filtering algorithms[19]. Through the analysis of battery cycle life test data, the instantaneous discharge voltage $V$ and its unit time voltage drop $V'$ can be used as model parameters to estimate SOH, which is linearly related to $1/V'$ multiplied by the correction factor[20].

4. Conclusion

The reasons for the battery aging and the estimation methods of SOH are discussed. In terms of battery SOH estimation, the model-based SOH estimation method has high accuracy and can be effectively combined with the chemical mechanism of the battery to explain the aging mechanism of the battery, but the modeling and parameter identification process is more complicated. Data-driven SOH estimation method can also achieve very good estimation results with the improvement of estimation algorithms and it has attracted widespread attention for it’s efficient and convenient application in vehicles BMS.

Acknowledgments

The author is very grateful to Professor Dafang Wang for his guidance and the support of the doctors in the laboratory!
References

[1] Dubarry M, Truchot C, et al. Synthesize battery degradation modes via a diagnostic and prognostic model[J]. Journal of Power Sources, 2012, 219(DEC.1): 204-216.

[2] Vetter J, P Novák, Wagner M R, et al. Ageing mechanisms in lithium-ion batteries[J]. Journal of Power Sources, 2005, 147(1/2):269-281.

[3] Jiang L, Li Q, Chen WR, et al. Study on parameter identification of third-order RQ equivalent circuit of PEMFC based on Nelder-Mead optimization[J]. Power Supply, 2019, 17(2):12-18, 25.

[4] Qian K, Huang B H, Ran A H, et al. State-of-health (SOH) evaluation on lithium-ion battery by simulating the voltage relaxation curves[J]. Electrochimica Acta, 2019(303):183-191.

[5] Fang L L, Li J Q, Peng B. Online Estimation and Error Analysis of both SOC and SOH of Lithium-ion Battery based on DEKF Method[J]. Energy Procedia, 2019(158):3008-3013.

[6] Lamorgese A, Mauri R, Tellini B. Electrochemical-thermal P2D aging model of a LiCoO 2 /graphite cell: Capacity fade simulations, 2018(20):289-297.

[7] Yang S C, Hua Y, Qiao D, et al. A coupled electrochemical-thermal-mechanical degradation modelling approach for lifetime assessment of lithium-ion batteries, 2019(326): 134928.

[8] Zhang X, Lu J L, Yuan S F, Yang J, Zhou, X. A novel method for identification of lithium-ion battery equivalent circuit model parameters considering electrochemical properties[J]. Journal of Power Sources, 2017, 345:21-29.

[9] Sheikh S S, Anjum M, Khan M A, et al. A Battery Health Monitoring Method Using Machine Learning: A Data-Driven Approach[J]. Energies, 2020(13):3658.

[10] Xia Z, Qahouj J. Adaptive and fast state of health estimation method or lithium-ion batteries using online complex impedance and artificial neural network[J]. Applied Power Electronics Conference and Exposition, 2019:17-21.

[11] Peng Y, Hou Y D, Song Y C, et al. Lithium-Ion Battery Prognostics with Hybrid Gaussian Process Function Regression[J]. Energies, 2018, 11(6):1420.

[12] Tian H, Qin P, Li K, et al. A review of the state of health for lithium-ion batteries: Research status and suggestions[J]. Journal of Cleaner Production, 2020, 261:120813.

[13] Chen Z P, Wang Q T. The Application of UKF Algorithm for 18650-type Lithium Battery SOH Estimation[J]. Applied Mechanics & Materials, 2014, 519-520:1079-1084.

[14] Zhou Y P, Miao H, et al. Lithium-ion batteries remaining useful life prediction based on a mixture of empirical mode decomposition and ARIMA model[J]. Microelectronics Reliability, 2016(65):265-273.

[15] Qu J T, Liu F, Ma Y, et al. A Neural-Network-Based Method for RUL Prediction and SOH Monitoring of Lithium-Ion Battery[J]. IEEE Access, 2019, 7(99):87178-87191.

[16] Weng C H, Cui Y J, Sun J, et al. On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression[J]. Journal of Power Sources, 2013(235):36-44.

[17] Li X Y, Wang Z P, Zhang L, et al. State-of-health estimation for Li-ion batteries by combing the incremental capacity analysis method with grey relational analysis[J]. Journal of Power Sources, 2019(410-411):106-114

[18] Li X Y, Wang Z P, Yan J Y. Prognostic health condition for lithium battery using the partial incremental capacity and Gaussian process regression[J]. Journal of power sources, 2019, 421(MAY 1):56-67.

[19] Tang X P, Zou C F, Yao K, et al. A fast estimation algorithm for lithium-ion battery state of health [J]. Journal of Power Sources, 2018(396):453-458.

[20] Huang S C, Tseng K H, Liang J W, et al. An Online SOC and SOH Estimation Model for Lithium-Ion Batteries[J]. Energies, 2017(10):512.