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A Review on State of Health Estimation for Lithium-ion Batteries

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Abstract: *As an important technology of battery management system, state of health estimation of lithium-ion battery is the basis of electric vehicle range estimation and predictive maintenance, and also an important parameter to help correct and improve the accuracy of state of charge estimation. The state of health estimation technique for lithium-ion batteries is reviewed and classified into direct and indirect methods, the advantages and disadvantages of different categories is described as well. What's more, health indicators for state of health estimation and their practicality is analyzed. Finally, it is pointed out that state of health estimation for lithium-ion batteries on electric vehicles should possess on-board practicality while ensure accuracy at varying wide temperature window.*

Keywords: *Electric vehicle, lithium-ion battery, state of health estimation, health indicator*

1. Introduction

Traditional fuel vehicles bring convenience to human life, but also cause energy crisis and environmental pollution. Therefore, countries around the world are actively committed to the research and promotion of new energy vehicles. In recent five years, the sale of new energy vehicles in China has increased sharply, with pure electric vehicles accounting for the largest proportion. Due to the high specific energy and long service life of lithium-ion battery, the pure electric vehicle mainly uses lithium-ion battery as the power source.

With the use of lithium-ion batteries on electric vehicles (EVs), some irreversible chemical reactions occur inside the batteries, resulting in cracks in the electrodes and loss of active materials of positive and negative electrodes, which lead to the aging of batteries. Battery aging results in decreasing of capacity, with continuous reduction of driving range. with the aging of batteries, its internal resistance is increasing, which is more likely to cause thermal runaway, spontaneous combustion and even explosion. Therefore, on-board State of Health (SOH) estimation is of great importance for ensuring occupant safety and reliable State of Charge (SoC) estimation. Thus, this paper reviewed SOH estimation methods for lithium-ion batteries to guide the on-board technique development for EVs.

2. Research status of SOH estimation for lithium-ion batteries

SOH represents the current health level of a battery and is the basis and prerequisite of life prediction. With the degradation of battery, capacity gradually decreases while internal resistance continuously increases, and hence capacity and internal resistance are commonly used as health indicators (HIs) for battery SOH. Battery capacity is a measure (typically in Ah) of the charge stored by the battery, and calculated by timing the discharge time with the constant discharge current which was acquired under certain specified conditions. As a result, the SOH is obtained with capacity and internal resistance as follows:

$$SOH = C_{now} / C_{rated} \times 100\% \tag{1}$$

$$SOH = \frac{R_{EOL} - R_{now}}{R_{EOL} - R_{new}} \tag{2}$$

Where C_{now} is the capacity at present, C_{rated} is rated capacity given by the manufacturer, R_{now} is the current internal resistance, R_{EOL} is the internal resistance at the end of life, and R_{new} is the initial internal resistance.

According to Equation (1) and (2), the SOH range of battery is 0~100%. The SOH of a new battery is 100% and it decreases continuously with the use of battery. When the battery performance declines to an extent that the basic operation of the equipment can not be maintained, it is considered that the battery has run out its life and needs to be replaced in time, and the SOH at this moment is called the failure threshold. Generally, scholars in the automotive industry choose 80% as the failure threshold. According to Equation (1) and (2), the battery SOH estimation includes capacity and internal resistance estimation as SOH can be obtained from capacity and internal resistance.

Waag et al. Classified battery capacity estimation methods into three categories: state of charge (SOC) - open circuit voltage (OCV)-based method, curve-based method and model-based method [1]. SOC-OCV based method is always accompanied with the equivalent circuit model (ECM). Curve-based method includes incremental capacity analysis (ICA) and differential voltage analysis (DVA), and model-based method is divided into electrochemical model and physical model-based method. Berecibar et al. divided SOH estimation method into experimental technique and adaptive model-based technique [2]. Experimental technique contains direct measurements and models based on measurements. The direct measurement method obtains the battery health indicator through measurement, while the models based on measurements extracts the health indicator based on electrical signal, and then SOH can be acquired. Different from the experimental technique, the adaptive model-based technique obtains the SOH by employing the ECM.

According to the references, we divide SOH estimation method into two categories: direct method and indirect method. The direct method uses the original or simply processed measurement to calculate the capacity or SOH, while the indirect method first needs extracting indirect health indicators from the measurement with complex calculation. The difference between the two types is shown in Fig.1.

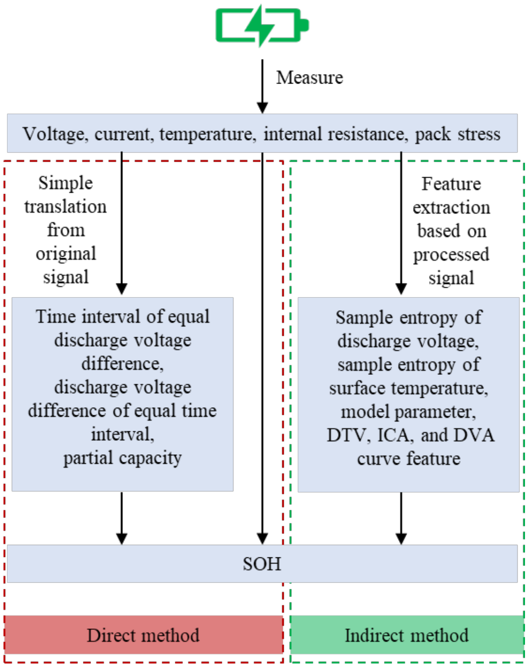

Figure 1: Classification of SOH estimation method for lithium-ion battery

2.1 Direct method

SOH can be estimated by internal resistance of battery [3], mechanical stress [4] between cells and Ampere hour integration [5]. Electrochemical impedance spectroscopy needs special instruments. Stress measurement needs to paste strain gauge on each battery. The Ampere hour integration tends to accumulate measurement error. Therefore, these three methods are not suitable for EVs on-board application.

Extracting health indicators based on current and voltage is one of the important methods to estimate SOH. Liu et al. extracted time interval of equal discharge voltage difference (TIEDVD) and discharge voltage difference of equal time interval (DVD_ETI) to estimate SOH based on linear model [6,7]. Although linear relationship between TIEDVD, DVD_ETI and SOH is strong in general, the linearity is weak when SOH is near 0 and 100%. Therefore, Zhao used nonlinear fitting function Support Vector Machine (SVM) to calculate SOH [8]. The increasement of the number of characteristic variables improves the estimation accuracy, and hence Zhang et al. extracted five variables including charge time and battery surface temperature, and used multi-core Relevance Vector Machine (RVM) to estimate battery SOH [9]. Some variables of the above methods are taken from the constant current discharge stage. As the EV' battery is not discharged with constant current, the method is not of universality, thus the above methods are not able to be applied on vehicles.

The practical applicability of SOH estimation method can be improved by extracting health indicators from charge stage. Feng et al. extracted the probability distribution function of charge voltage sampling points and estimated SOH with the number of sampling points in a certain voltage interval [10]. However, the accuracy of SOH is affected by sampling accuracy, noise and data smoothing technology. Chen et al. extracted the charge time, energy and electric quantity of fixed voltage interval as the input of SVM to estimate SOH without considering the influence of temperature [11]. Hu et al. input the initial charge voltage, charge cutoff voltage, charge cutoff current, charge cutoff voltage, constant current charge quantity and constant voltage charge quantity into k-nearest neighbor regression to estimate the capacity [12]. However, technique in reference [12] need the battery to be fully charged and discharged, so it cannot be applied on vehicle.

Internal resistance and capacity can be identified as a variable in state-space representation derived from battery ECM. Based on first-order RC ECM, Kim estimated the battery capacity with a double-sliding-mode observer [13]. In order to improve accuracy, Guo et al. used nonlinear least square method to identify battery capacity [14]. To improve the dynamic performance of parameter identification, recursive least square method with forgetting factor (LSMFF) was used to identify battery internal resistance [15]. Kalman filter (KF) and other methods evolved from were also common parameter identification method when using ECM. Hu et al. used double EKF to update battery capacity at macro scale and estimate battery SOC at micro scale [16]. Combining three-dimensional capacity-SOC-OCV surface and Thevenin battery model, Xiong et al. used dual adaptive KF to estimate battery SOC and capacity [17]. Compared with KF and UKF, particle filter is not constrained by linear or Gaussian distribution, and has better reliability and accuracy, but it possesses the disadvantage of particle degradation. Based on the battery ECM, Yang et al. employed genetic algorithm (GA) with objective function, which is sum of terminal voltage error squares, to estimate the battery capacity [18]. However, the parameter identification of battery ECM depends on the SOC-OCV curve, and the SOC-OCV curve drifts due to change of temperature. Therefore, the SOH estimation method based on the battery ECM can only be implemented at a specific temperature, and it is not robust when used on EVs.

Considering the effects of temperature on SOC-OCV, Remmlinger established a linear variable parameter state space model, and then used the central differential Kalman filter to identify the battery internal resistance [19]. Chaoui [20] identified the parameters of Thevenin battery ECM based on adaptive control theory, and added temperature compensation term to revise estimated internal resistance. Although Remmlinger and Chaoui considered the ambient temperature, the method with battery ECM needs to update the parameters all the time in the whole data acquisition stage and thus is time-consuming.

The loss of active material (LAM) and loss of lithium-ion (LLI) affect the electrode voltage curve, causing the voltage curve to change with the increase of LAM and LLI. Therefore, voltage curve reconstruction is an effective method to quantify LAM and LLI. Ma et al. used particle swarm optimization (PSO) to identify the degree of LAM and LLI by comparing the reconstructed voltage curve with real voltage, and then determined SOH [21]. However, this method requires constant current discharge, takes a long time, and is affected by temperature, and hence it cannot be used within EVs' battery management system (BMS).

By applying direct method, the SOH can be obtained quite straightforward with original or slightly deformed measurement, causing the estimation process quite time time-saving, except for ECM-based technique which has high accuracy.

2.2 Indirect method

Indirect health indicators are usually extracted from the normal charging/discharging voltage and current. Widodo et al. extracted the sample entropy of discharge voltage, and quantified the mapping relationship between sample entropy and capacity with Support Vector Machine (SVM) and RVM [22]. SVM is sensitive to parameter adjustment and function selection, and RVM has greater sparsity, but the training time is greatly increased. Li et al. employed probabilistic finite state automata and wavelet transform to obtain a health indicator named feature difference so as to make SOH estimation [23]. However, health indicator extraction takes many steps and hence causes this technique time-consuming. Li et al. applied polynomial to fit the battery surface temperature sample entropy versus SOH curve [24]. This method exhibits slight computing-burden, but requires constant current discharging. Lu et al. input constant current charging time, maximum curvature of voltage during constant voltage charging, constant voltage charge quantity and discharge voltage drop into Laplacian Eigenmap to obtain SOH [25], which requires the battery to be fully charged and cannot be applied on EVs.

Indirect health indicators can also be extracted by exerting special operating mode to battery. Cai et al. first applied “Hotel pulse” current profile on battery, and then indirect health indicator was extracted based on fast wavelet transform and cross D-Markov machine to represent SOH [26]. Hu extracted sample entropy of voltage sequence under hybrid pulse power characterization profile, and then calculating SOH by a cubic function [27]. Piao tested battery under economic commission for Europe and extra urban driving cycle, and determined the abnormal points in the operation data based on the angular distribution outlier detection method so as to estimate SOH [28]. The above methods all apply special profile on battery, but these methods are impractical for on-board circumstance due to the lack of testing equipment.

Differential thermal voltammetry (DTV), ICA and DVA are alternative technique to estimate SOH. Wu et al. found DTV curve peak value and its position moved linearly with the aging of battery, and then employed Savitzky-Golay to smooth the temperature curve so as to improve estimation accuracy [29]. Goh estimated SOH based on linear relationship between capacity and the time difference from first peak of the DVA curve to the end of constant current charging [30]. ICA curve peak position and peak value were used to estimate SOH by SVM and linear regression [31]. Lorentz function, Gaussian function, Gauss vertex function, pseudo-Voigt peak function and Daubechies wavelet can be used to smooth the ICA curve so as to improve estimation accuracy. Wang et al. optimized the DVA curve with center least squares method and so-called local data symmetry method, and then estimated the SOH according to the linear correlation between two inflection points’ distance and capacity [32]. Different smoothing method and sampling frequency cause different DTV, DVA, ICA curve, indicating the performance of these methods is not stable. What’s more, the imperative of constant current discharging induces these methods not practicable for on-board application.

Indirect health indicators can be extracted from battery electrochemical model as well. Prasad et al. derived the transfer function of electrochemical model, and used least square method to identify diffusion time which is one of the transfer function parameters so as to estimate SOH based on a linear correlation between it and capacity [33]. Lee et al. found the solid-phase diffusivity in the electrochemical model declines monotonously with battery aging, thus solid-phase diffusivity was used to estimate SOH [34]. Electrochemical model involves chemical reactions, and it is theoretically impossible to describe and quantify all the reactions in the battery without error. Moreover, the process of parameter identification is still difficult and time-consuming for BMS CPU. Therefore, this method cannot be applied on-board.

The battery ECM can also be used to extract indirect health indicators. Yang et al. also estimated SOH based on linear correlation between time constant and capacity with Thevenin battery model [35]. Zhang et al. established a battery ECM including two capacitors and three resistors, and found one capacitance was linearly related to the battery capacity [36]. The indirect health indicators extracted from ECM mostly have linear correlation with SOH, which makes SOH estimation quite simple. However, as battery internal resistance change with SOC, other parameters change as well with charging and discharging battery. Thus, this method needs to consider the SOC so as to improve the estimation accuracy.

It takes more effort to dig and extract indirect health indicators than health indicators. However, it's hard to say which category is better than the other, but the superiority of a technique hugely depend on three factors- the feasibility to extract the health indicator, the quality of health indicator, and mapping functions used to calculate SOH. The feasibility to extract the health indicator measures the degree of difficulty to calculate health indicators, and whether the health indicator is available for on-board usage. The quality of health indicator, which is the most important factor for a good SOH estimation method, is measured by health indicator’s correlation with SOH, and high correlation means good quality. The mapping functions are chosen to calculate SOH after selecting the health indicator. The relationship between SOH and health indicator determines the mapping function to be used, but a good choose of mapping function improves SOH estimation accuracy than other available methods.

The advantages and disadvantages of some mentioned methods are shown in Table 1.

Table 1: Advantages and disadvantages of some SOH estimation methods

	Health indicators or methods	Algorithm involved	Advantage	Disadvantage
Direct method	Internal resistance by electrochemical impedance spectroscopy[3]	Linear regression	Calculation is simple and time-saving	Special test equipment is required
	Battery pack stress[14]	Linear regression	Calculation is simple and time-saving	Strain gauge causes additional cost
	Starting voltage, cut-off voltage and current, constant current charge and constant voltage charge[12]	*k*-nearest neighbor regression	High accuracy	Fully charging or discharging is rare
	Internal resistance or capacity by ECM	Kalman filtering[30]	SOC and SOH can be estimated simultaneously	Iterative update causes huge amount of calculation
	Reconstruction of voltage curve[21]	Particle swarm optimization	Explaining the mechanism of battery degradation	Time-consuming and needs constant current charging or discharging
	Time interval of equal discharge voltage difference[6]	Linear regression	Calculation is simple and time-saving	Low accuracy
	Discharge voltage difference of equal time interval[7]	Recurrent neural network Support vector machine	High accuracy	Needing much data for training
	Average temperature during charge, average temperature during discharge, cutoff voltage[9]	Relevance vector machine	High accuracy	Needing complete constant current discharge and same temperature with test
	Charge time, energy and partial capacity in fixed voltage range[11]	Support vector machine	High accuracy	Needing complete constant current discharge and hug amount of training data
	Sample entropy of discharge voltage[22]	Support vector machine	Only needing little voltage data	Constant current discharge is required
	Time constant[35]	Linear regression	Simple calculation	Needing fully charging and less accurate
	ICA [31], DTV [29], DVA curve[30]	Linear regression	Simple calculation	Needing constant current discharge and less accurate
Indirect method	Time constant and internal resistance of electrochemical model[33]	Linear regression	High accuracy	Complicated and time-consuming
	Solid phase diffusion coefficient of electrochemical model[34]	Linear regression		
	Sample entropy of battery surface temperature in charge stage[34]	Polynomial function	Only needing little temperature data	Environment temperature affects accuracy
	Constant current charge time, maximum curvature of constant voltage charge voltage, constant voltage charge quantity and discharge voltage drop[25]	Laplacian Eigenmap	Moderate accuracy	Needing a lot of training data
	Voltage sample entropy of hybrid pulse power characteristic test[27]	Cubic function	Simple calculation	Special charging and discharging profiles are required

3. Conclusion

State-of-art of SOH estimation method for lithium-ion batteries is introduced, and their pros and cons for on-board application is also analysed. Though the endless invention of SOH estimation method improves estimation accuracy, some problems to be addressed are as follows:

(1) Some health indicators are not practical, so the corresponding SOH estimation method cannot be applied on EVs.

Because EVs power battery is not discharged by a constant current, the health indicators extracted from the constant current discharging condition are not applicable for on-board application. Although the charging strategy of electric vehicle is fixed, the constant current charging time and constant voltage charging time extracted from the charging phase can only be obtained by near fully charging and discharging, and hence the method cannot be implemented on EVs. Therefore, considering the depth-of-discharge and usage conditions of batteries is indispensable for making robust SOH estimation.

(2) The accuracy and robustness of SOH estimation with temperature compensation needs to be further improved. Although some methods have incorporated temperature into SOH estimation, their employment condition lies in a narrow temperature window, and estimation accuracy huge suffers from higher or lower temperature. Therefore, a SOH estimation method suitable for wide temperature range is yet desirable.

(3) Database of lithium-ion batteries of EVs needs more data. Although the Chinese ministry of industry and information technology requires enterprises to transmit the operation data of EVs to the database, the transmitted data of batteries is not complete. In terms of battery voltage, only the battery pack voltage and the maximum and minimum cell voltage are transmitted, causing the lack of valuable cell voltage, which is base for monitoring cell safety and operation status. Therefore, it is challenging to estimate SOH of individual cell in battery pack.

(4) An accurate SOH estimation of battery pack still needs more effort. At present, the research on SOH estimation of battery pack is far less than cell and module, and the definition of battery pack SOH has not reached a consensus. The battery pack is usually composed of hundreds of cells. Due to the inconsistency of individual cells, defining a generic and reasonable SOH of battery pack is quite difficult. In practical application, the environment of battery pack is complex and the working conditions change always. Therefore, it is urgent to develop a robust and adaptive SOH estimation method for battery pack.

The slow aging process of lithium-ion batteries reduces the timeliness requirement of SOH estimation, thus future research should be focused on time-consuming physical-electrochemical model coupling data-driven method as a result of pursuing highly accurate estimation. In addition, with the rise and development of big data and cloud computing, the running speed of complex algorithms will be boosted quite a lot, while ensuring the timeliness and accuracy of SOH estimation results.

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