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Review on State of Charge Estimation Methods for Li-Ion Batteries

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The state of charge (SOC) is an important parameter in a battery-management system (BMS), and is very significant for accurately estimating the SOC of a battery. Li-ion batteries boast of excellent performance, and can only remain at their best working state by means of accurate SOC estimation that gives full play to their performances and raises their economic benefits. This paper summarizes some measures taken in SOC estimation, including the discharge experiment method, the ampere-hour integral method, the open circuit voltage method, the Kalman filter method, the neural network method, and electrochemical impedance spectroscopy (EIS. The principles of the various SOC estimation methods are introduced, and their advantages and disadvantages, as well as the working conditions adopted during these methods, are discussed and analyzed.

Keywords: Li-ion battery, State of charge, Principle

1. INTRODUCTION

A battery, as a type of energy-storage equipment, boasts of stable voltage and being a reliable power supply. Battery energy storage systems are extensively applied to such fields as micro-grids, uninterrupted power supplies (UPS), and electric automobiles. In a micro-grid, a battery energy-storage system can provide grid connection power adjustment and peak regulation, isolated power grid operation, improvement of power quality, promotion of micro-power source performances, and other related functions [1-3]; and is a core component of a UPS, an electric automobile, and other applications. Batteries are usually connected in series to form a battery pack to satisfy requirements for high voltage and large capacity; during usage, because of differences in the performance of each single battery, ambient temperature changes, excessive charge and excessive discharge, and other factors, the performance of a battery pack depends on the single battery within the pack that performs the worst; hence the service life of a battery pack is usually shorter than the service life of single batteries as provided by their manufacturers. If a battery pack is used extensively without any management measure, its performance will deteriorate quickly to an unserviceable state earlier than scheduled. Therefore, a reliable battery-management system (BMS) is needed to carry out effective management of the battery [4-6]. BMS can increase the service efficiency of a battery, extend the service life, lower the operating cost, and raise the reliability of the battery pack. The main functions of a BMS include control of the battery's charge and discharge, battery parameter measurement (voltage, current, temperature, etc.), battery pack equivalence control, state of charge (SOC) estimation, battery service-life estimation, and failure diagnosis, where SOC estimation is the core and a difficult point in research on BMS. An accurate SOC can be important for battery charge and discharge control and battery equivalence, and for a battery used in an electric automobile, SOC can also indicate the remaining mileage accurately.

The SOC is a number indicating the remaining power in the battery and is an important parameter of the battery, but the SOC

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of a battery cannot be measured directly by a sensor; it is indirectly estimated via various algorithms. Li-ion batteries are one of the best chemical batteries by far, boasting of high service voltage, small volume, light weight, high energy density, zero memory effect, low self-discharge rate, long cycle life, and other merits [7], but only an accurate estimation of a Li-ion battery's SOC can give full play to its power performance [8], prevent impacts to its safety and service life resulting from excessive charge and discharge, and maximally guarantee its reliable operation, so that the cost can be lowered and the economic benefit raised.

This article summarizes traditional SOC estimation methods, i.e., the discharge experiment method, the ampere-hour integral method, the open circuit voltage method, the internal impedance method, a new intelligent algorithm (namely, the Kalman filter method), the artificial neural network method, and electrochemical impedance spectroscopy, with discussion of their advantages and disadvantages in application.

2. DEFINITION OF THE SOC

The SOC of a battery reflects its residual capacity, which is, at a certain discharge rate, the ratio of the present battery residual capacity to its overall available capacity. Its mathematical expression is [9]

$$SOC = \frac{Q_t}{Q_o} \times 100\% \tag{1}$$

where Q_t is the residual power of the battery at the time of calculation, and Q_0 is the overall capacity of the battery. When the battery is fully charged, SOC = 1; when the battery is fully discharged, SOC = 0. With a change of the discharge rate, the corresponding rated capacity also changes. Based on the definition, when the battery is under different working conditions, Q also changes.

3. TRADITIONAL SOC ESTIMATION METHODS

3.1 Discharge experiment method

The discharge experiment method refers to a Li-ion battery that is discharged at a constant current for a certain duration [10]. The discharged current is multiplied by the duration to get the discharged power, and the ratio of the power to the overall available capacity of the Li-ion battery for a corresponding current is the battery's SOC before discharge. The discharge experiment method is by far the most accurate and most reliable SOC estimation method. It is usually used in the laboratory, and applies to various kinds of secondary batteries. However, it suffers from two disadvantages: first, its long discharging duration; second, the fact that the battery is out of service during the discharge. Therefore, the discharge experiment method is not suitable for online SOC estimation. Usually, the method is used as a calibration method in SOC estimation, and is mostly used in lab analysis, testing, and research.

3.2 Ampere-hour integral method

The ampere-hour integral method is a classic SOC estimation method [11-13]. It is also called Coulomb counting, and is by far the most extensively used method in BMS. It calculates the discharged or charged power of a battery by means of continuous monitoring of the battery and calculation of its integral, with no consideration of internal structure or chemical-state changes of the Li-ion battery. The expression to estimate SOC with the ampere-hour counting method is

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_0) + \frac{1}{Q_N}\int_{t_0}^{t} \eta(t) \times I(t)dt \tag{2}$$

Where $SOC(t_0)$ is the state of charge at time t_0; I(t) is the charged (positive value) or discharged (negative value) current; Q_N is the rated capacity of the battery; and η(t)is the compensation coefficient, which is used to compensate for influences of such factors as temperature, charged and discharged rate, aging, or self-discharge rate. The ampere-hour integral algorithm is simple, stable at work, and easy to use from an engineering perspective. It is an open-loop algorithm, where the error of the current testing signal accumulates in the SOC estimation value, and the accumulated error grows larger gradually with the increase of the charged and discharged cycles. It is quite difficult to discover the compensation coefficient η(t), especially when taking aging and self-discharge rate into account. Therefore the method has the following disadvantages:

(1) it requires a fairly high current testing frequency and accuracy, otherwise it will increase the integral error;

(2) the battery's charge and discharge efficiencies are related to its SOC value, current, temperature, aging, impedance change rate, service life, and other factors, so it is difficult to measure accurately, resulting in the gradual increase of the SOC estimation error, and then the accumulated error;

(3) in situations of high temperature or drastic current fluctuations, the battery capacity will change, and the method cannot easily yield an accurate result.

In conclusion, the method has measurement errors when charging and discharging current fluctuates widely, so it easily leads to accumulated SOC errors and cannot take full consideration of the battery's efficiency on charge and discharge. Moreover, the error becomes larger when the temperature and the load fluctuate drastically. Such issues as the battery's self-discharge, charge-discharge efficiency, and accurate measurement of current are the difficulties with the ampere-hour method.

3.3 Open circuit voltage method

Researchers have shown that, when a Li-ion battery is at a static state, its open-circuit voltage (OCV) is related to the SOC, basically, at a monotonic increasing trend. Therefore, the SOC can be estimated by means of the OCV [14-16]; it can be measured directly and thus is the simplest method for SOC estimation. But the Li-ion battery has to be left unused for a long time in order to ensure its OCV has reached a steady value, from which the OCV-SOC relationship can be estimated more accurately. The SOC can also be estimated by estimation of the battery's electromotive force; therefore, the method is only applicable when the Li-ion battery is at a static state.

4. NEW INTELLIGENT ALGORITHM

4.1 Kalman filter method

The Kalman filter method [17-25] is a mature technology for status estimation of dynamic positioning, control of dynamic systems, navigation and communication technologies, and other applications. In recent years, the Kalman filter has also been used to estimate the Li-ion battery SOC. The Kalman filter consists of a group of recursive equations that perform evaluations repeatedly when the system is in operation. There is no need to consider many past input signals; only the last input signal is needed when each recursive equation is performed.

Figure 1 shows the Kalman filter block diagram. U(k) is the known input vector of the system; B(k), A(k), C(k), and D(k) describe the dynamic of the system; W(k) and V(k) are independent zero-mean Gaussian white noise; and Y(k) is the output vector of the system. The Kalman filter status equation and observation equation for the Li-ion battery model are as follows:

$$X(k+1)=A(k)X(k)+B(k)U(k)+W(k) \tag{3a}$$

$$Y(k)=C(k)X(k)+D(k)U(k)+V(k) \tag{3b}$$

$X(k)$ is the status vector at time K, $U(k)$ is the input vector of the system, $W(k)$ and $V(k)$ are none inter-related zero-mean Gaussian white noise, $Y(k)$ is the output vector of the system, and the assumption is:

$$E[W(n)W(k)^T]=\begin{cases}\sum_W,(n=k)\\0,(n\neq k)\end{cases} \tag{4a}$$

$$E[V(n)V(k)^T]=\begin{cases}\sum_V,(n=k)\\0,(n\neq k)\end{cases} \tag{4b}$$

where E[*] indicates the mathematic expectation, and T is the transposition of the matrix. Even though W (k) and V(k) do not meet the assumption in reality, the system can still work well because of the robustness of the Kalman filter [26]. The system has to be initialized before the Kalman filter:

$$\hat{X}(k)^+=E[X(k)] \tag{5a}$$

$$\sum\nolimits_k^+ =E\{[X(k)-\hat{X}(k)^+][X(k)-\hat{X}(k)^+]^T\} \tag{5b}$$

The initialization is usually not accurate, but that does not affect the Kalman filter, because the system will converge quickly after several rounds of recursive operation. The Kalman filter estimates the status value, system output, and error covariance matrix at each sampling interval $\hat{X}(k)^-,\hat{Y}(k)^-,\sum_k^-$.

$$\hat{X}(k)^-=A(k-1)X(k)^+ +B(k-1)U(k-1) \tag{6a}$$

$$\sum\nolimits_k^- =A(k-1)\sum\nolimits_{k-2}^+ A(k-1)^t+\sum\nolimits_W \tag{6b}$$

Then the observed value is used to update the status value and the error covariance matrix $\hat{X}(k)^+,\sum_k^+$.

$$\hat{X}(k)^+=\hat{X}(k)^- +L(k)\{Y(k)-C(k)\\ [\hat{X}(k)^- +D(k)U(k)]\} \tag{7a}$$

$$\sum\nolimits_k^+ =[I-L(k)C(k)]\sum\nolimits_k^- \tag{7b}$$

The updated status value after the measurement equals the estimated status value plus the Kalman gain L(k) multiplied by the difference between the actual value and the estimated value, and the Kalman gain L(k) can be calculated by the following equation:

$$L(k)=\sum\nolimits_k^- C_k^T[C_k\sum\nolimits_k^- C_k^T+\sum\nolimits_V^-]^{-1} \tag{8}$$

If the present estimated status value has a comparatively large deviation, it will lead to a larger $\sum_k^-$, which further enlarges L(k), and the updated status value $\hat{X}(k)^+$ after the measurement will be larger; a smaller $\sum_k^-$ leads to a smaller L(k), and the updated status value $\hat{X}(k)^+$ after the measurement will be smaller. Similarly, if the observation noise V(k) is comparatively large, $\sum_V$ will become larger and L(k) smaller; therefore, the Kalman gain L(k) correlates to the signal-noise ratio; when the signal-noise ratio is low, the Kalman gain is small, and if the signal-noise ratio is high, the Kalman gain is large.

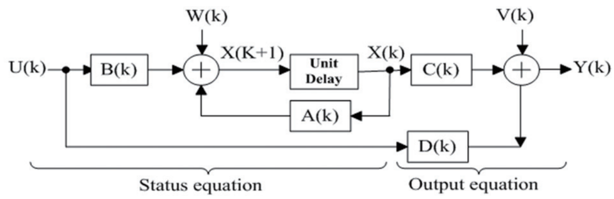

Fig. 1. Kalman filter Block diagram for SOC estimation.

Generally speaking, the Kalman filter can strongly repress noise and correct initial errors, and thus can be used to evaluate the estimation error; on the other hand, the Kalman filter depends on the accuracy of the model and the parameters, and because the Li-ion battery is nonlinear, the Kalman filter method may generate linear errors.

4.2 Artificial neural network method

The Artificial neural network (ANN) is a computational structure that imitates the human brain neuron systems; it can imitate the information processing, memorizing, and learning processes of the human brain. The neural network is basically nonlinear, can provide a nonlinear output in response to an external stimulation, thus can better simulate the nonlinear dynamics of batteries [27-31], and can therefore be used for SOC estimation. Neural networks used for such SOC estimation include the back propagation (BP) neural network model and the radial basis function network (RBF). The BP model is one of the most widely applied models, based on the most comprehensive theories. It can learn during the training process, is more effective in modeling the system of complicated dynamic behaviors, and, because of its multi-input and nonlinear characteristics, can simulate the external characteristics of batteries. A BP neural network, shown in Fig. 2, usually adopts a 3-layer structure, namely, the input layer, the hidden layer and the output layer. The number of neurons in the input layer depends on the actual demands; these neurons connect the network with its external environment, and send input signals to the hidden layer. In a BP neural network with artificial neurons used for SOC estimation, as shown in Fig. 2, the input variables are voltage, current, temperature, etc., and the output is the SOC of the battery. The number of neurons in the hidden layer depends on the complexity and analytical accuracy of a case. These neurons are responsible for the nonlinear transformation from the input space to the hidden space. The output layer realizes the mapping from a high-dimensional space to a low-dimensional space. The disadvantage of the neural network method is its demand for large, comprehensive quantities of data to train the system, and its estimation errors result mainly from the selected training data and the training method.

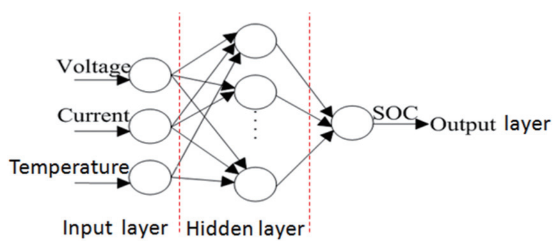

Fig. 2. BP neural network with artificial neural network used for SOC estimation.

4.3 Electrochemical impedance dpectroscope method

Electrochemical impedance spectroscopy (EIS) [32-34] is a method for studying Li-ion batteries in which small-amplitude sine waves (voltage or current) are used as the disturbing signal. The battery generates a response that is like a linear relationship, and the impedance spectroscope measures it over a very wide frequency range. Fig. 3 shows an EIS Test Diagram. The EIS measurement of a Li-ion battery system approximates a stable linear system M. A sine-wave signal X (voltage or current) with angular frequency ω is input into the system, and a sine-wave signal Y (current or voltage) with angular frequency ω is output from the system. The frequency response function G of the Li-ion battery is then the electrochemical impedance, which is also a function of angular frequency ω.

$$Y(\omega) = G(\omega)X(\omega) \tag{9}$$

A series of frequency response functions with different angular frequencies can be measured, and are therefore the EIS of the Li-ion battery. Based on the measured EIS spectroscopy, the EIS equivalent circuit or mathematical model can be calculated; it is found by analysis of EIS when the Li-ion battery is at different SOCs. When the internal impedance of the Li-ion battery changes from capacitive to inductive, the corresponding disturbing signal frequency has a monotonic relationship with its SOC, based on which the Li-ion battery's SOC can be rapidly estimated [35-40]. The electrochemical impedance spectroscope, a type of frequency domain measurement, is used to study the Li-ion battery system by measurement of the impedance over a very wide frequency range, and thus can acquire more dynamic and structural information than other measurement systems can.

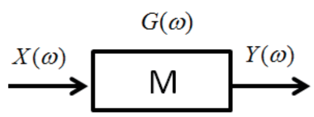

Fig. 3. EIS Test Diagram.

5. SUMMARIES

This paper has summarized and studied the methods used to estimate Li-ion battery state of charge, and compares several SOC estimation methods, as shown in Table 1.Some conclusions are as follows.

(1) There are quite a few SOC estimation methods, but in actual application, the ampere-hour integral method is the one most frequently used.

(2) Of the current SOC estimation methods, all have their pros and cons. The ampere-hour integral method, in combination with the OCV method, is widely adopted to estimate SOC, because it can reduce the accumulated error effectively, but fails to deal with the root causes of such accumulated error.

(3) Since the battery's charge and discharge current, terminal voltage, temperature, self-discharge, degree of aging, and other related factors influence the battery's capacity, such factors should be taken into consideration in SOC estimation. The BMS has rich storage of processing data, but the data are not used effectively. How to combine these data with data mining, data fusion, and other related technologies will be an effective way to estimate SOC and other parameters.

(4) Though the new intelligent algorithm is accurate in estimating SOC, it needs to be simplified in order to make engineering applications easier.

(5) It is still difficult to accurately estimate SOC when a Li-ion battery's current is changing, which could be a topic for further research..

Table 1. Comparison of SOC estimation methods.

SOC estimation method	Advantage	Disadvantage
Discharge experiment	Simple, accurate	Offline testing, time-consuming
Ampere-hour integral	Simple, online testing	Have accumulated errors
Open circuit voltage	Simple, online testing	Long duration standing required
Kalman filter	Online testing, high accuracy, suppresses noise interference	Complicated, dependent on the accuracy of the model
Artificial neural network	Online testing	Training with large quantity of data
Electrochemical impedance spectroscopy	Online testing	Subject to external conditions

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