American Research Journal of Computer Science and Information Technology
ISSN: 2572-2921
Volume 4, Issue 2, pp: 1-12

Research Article Open Access

Review of SOC Estimation Methods for Power Battery

Xi-Feng HE, Chang-Jiang DENG, Xing-Mao Liu
Chengdu University of Information Technology, Chengdu, Sichuan, China, 610225.

Abstract: The accurate state of charge(SOC) estimation of power battery is one of the core technologies of battery management system(BMS), which can effectively avoid overcharging and overdischarging, improve the service life of power battery, and also provide the guarantee for the safety operation of electric vehicles(EVs). By studying the methods of SOC estimation, the advantages and disadvantages and application of various estimation methods are analyzed in this paper.

Keywords: Power battery; battery management system (BMS); state of charge (SOC) estimation

Introduction

With the increase of energy shortage and environmental pollution, electric vehicles(EVs) have become the first choice for green transportation. As an important part of EVs, one of the core technologies of battery management system (BMS) is the accurate estimation of state of charge (SOC). SOC is an important parameter, which reflects the state of power battery, and determines the cruising distance of EVs. The accurate estimation of SOC is beneficial to the improvement of the service life of battery, the energy utilization efficiency, the operation cost and the safety, and the performance of the whole vehicle. But SOC is related to many factors such as temperature, charge/discharge state, polarization effect. It is difficult to realize the estimation of the remaining electric quantity of the battery from the internal mechanism reaction.

Defination of SOC

SOC represents the remaining power or energy of the battery, and it is defined in two ways. One is defined from an energy perspective by Korea Kia, which is as follows:

$$SOC = 1 - \frac{Wh}{Wh_e} \tag{1}$$

where Wh is the remaining available capacity,Wh_e is the total available energy.

At present, it is widely used to define SOC according to the amount of electricity in domestric and aboard. SOC is defined as the ratio of the remaining power to the rated capacity under the same conditions at a certain discharge rate in the experiment manual of EV by United States Advanced Battery Consortium(USABC). It is expressed as follows:

$$SOC = \frac{Q_c}{Q} = 1 - \frac{Q_{dis}}{Q} \tag{2}$$

where Q_c is the remaining power; Q_{dis} is the discharge power; Q is the rated capacity.

Formula (2) is the most simple and ideal definition of SOC. The estimation of the actual SOC is also influenced by a variety of factors, such as the operating environment temperature, the number of cycles of charge/discharge, the discharge rate, the charge/discharge cut-off voltage, etc.

For the battery capacity,temperature is the most important and common factor, mainly through affecting the internal chemical reaction of the battery to change the capacity. The normal range of working temperature should be 10° to 40°, and the temperature should be increased, which can properly increase the battery capacity, but too high temperature will damage the battery and lose the energy storage characteristics.

Primary cycle refers to the time of one charge and one discharge.With the increase of cycle times, the battery ages gradually and the storage performance decreases gradually.

From the fact that the discharge rate is equal to the discharge current divided by the rated capacity, it can be seen that the larger the discharge rate is, the smaller the battery capacity is.

Considering the above factors, SOC can be modified to be defined as

$$SOC_D = SOC_B K_W f(I) \tag{3}$$

where SOC_D, called dynamic charging state,is the battery state of charge affected by discharge current and temperature; SOC_B is the SOC under constant temperature and constant discharge current, K_W is the influence factor of temperature ,which can be obtained by experiment; I is the actual steady current.

SOC Estimation Methods

Direct Methods

Coulomb Counting Method(CC)

This method is usually used to estimate the electric quantity in the course of battery operation. It is a research method of battery charge state for hybrid electric vehicle proposed by Technical Research Center of CHUGoKU Electric Power Co.Inc. in Japan. The percentage of changing electric quantity is calculated by calculating the integral of current and charge/discharge time over a period of time, and then the difference between the initial SOC and the changed SOC is obtained, that is, the residual capacity SOC. The dedinition of SOC is as follows:

$$SOC = SOC_0 - \frac{1}{C_N}\int_0^t \eta I d\tau \tag{4}$$

where SOC_0 is the initial SOC; C_N is the battery capacity; η is the Charge and discharge efficiency; I is the charging/ discharging current.

This method only collects time and current from the outside, and does not consider the influence of battery temperature, charge-discharge rate, aging and other factors on the state of the battery, so the precision is extremely low. At the same time, the error of current measurement will also cause the error of SOC estimation to accumulate with time. In addition, the accuracy of the initial value of SOC will also affect the accuracy of SOC estimation, and the self-discharge phenomenon of battery will also affect the result of SOC estimation. It is generally necessary to combine the safety-time integration method with other algorithms to improve the accuracy of Ah algorithm.

Open-Circuit Voltage Method(OCV)

The open-circuit voltage method is often used to estimate the initial SOC value of batteries. This method is proposed by Japanese EV project Department, DENSO Corporation. Because the terminal voltage of the battery has relatively fixed functional relationship with SOC under the condition of long standing for a long time, SOC can be estimated according to the open circuit voltage.

OCV method is simple and easy to implement, and the measurement accuracy is high after the battery is standing for a long time. However, the significant shortcomings of OCV are shown in two aspects. First, the battery must be static for a long time before the terminal voltage can reach a stable state, but due to the frequent start and stop of electric vehicles, the working current changes greatly. Therefore, the terminal voltage can not be stable in a short period of time, so the SOC can not be estimated accurately in real time. Second, due to the existence of voltage platform, such as lithium iron phosphate battery, during the period of 30% ~ 80% of SOC, the curve of terminal voltage and SOC is approximately straight line, and the range of voltage variation is very small. The current hardware technology can not guarantee the accuracy of voltage measurement, and the error of SOC is very large during this period. OCV is generally used in combination with other methods to improve the estimation accuracy of SOC.

Discharge Test Method

Discharge test method is one of the most accurate and reliable estimation methods. The working principle of the experimental method is that the test equipment is set to discharge the battery with a certain current, and the discharge state continues until the end of the cut-off voltage. The product of current and discharge period is the residual electric charge of the battery at this time. This test method is the most simple and suitable for various types of batteries, and has high accuracy for different types of battery. However, this method also has some defects: the state change of battery must be monitored for a long time, and the battery must be in a static state at the same time. This method can not estimate SOC of the running battery. In practice, this method can be used as one of the references for battery maintenance, and can obviously judge whether the battery is effective or not. At the same time, this method is used as the reference standard of battery SOC in the experimental research, compares the accuracy of new SOC estimation methods, and evaluates the feasibility and rationality of new estimation algorithms.

Internal Resistance Method

The internal resistance method is to predict SOC, according to the relationship between the internal resistance of the battery and SOC. The internal resistance of the battery can be divided into AC internal resistance (AC impedance) and DC internal resistance (DC impedance), which are closely related to SOC.

The internal resistance of battery is also affected by various factors, and the variation range of the internal resistance is different in different working phases of the battery. Therefore, when this method is used to estimate SOC, the difficulty is relatively large, and the reliability is not high. In practical application, this method is suitable for estimating SOC in the late stage of discharge, and it is generally used in combination with the CC method.

The first three methods realize the estimation of SOC by measuring voltage and current physically in the above foure methods. The three methods are simple but the accuracy is poor. Among them, CC method can not solve the cumulative error problem, OCV method and discharge test method are widely used in the laboratory. The discharge test method is used to measure the remaining electricity and it is only suitable for SOC prediction of EVs under the condition of parking, but can not be predicted online. Due to the influence of battery type, quantity and consistency, internal resistance method is rarely used in electric vehicles.

Online Nonlinear Filtering Algorithm and State Observer Method Based on Model

Kalman Filter and its Derivative Algorithms

The Kalman Filter (KF) and its derivative algorithms are based on KF algorithm. KF is obtained from the knowledge of the probability theory. KF is composed of two parts. One is the actual battery system, its internal state is unknown, but the external output value and input system value can be measured.The other is the mathematical model established by the actual system, which uses the error between the output value of the modeling system and the actual system to correct the predicted value of the model system and optimize the optimal solution.

The system can be divided into the state equation and the observation equation under the condition of knowing the first probability of the system by calculating the minimum error of the system state by the processing of the measured value. The state equation and the observation equation are as follows.

State equation of discrete Kalman filter is as follows [2]:

$$x_{k+1} = A_k x_k + B_k u_k + \Gamma_k \xi_k \tag{5}$$

Observation equation of discrete Kalman filter is as follows [2]:

$$y_k = C_k x_k + D_k u_k + \eta_k \tag{6}$$

where x_k is state vector; y_k is observation vector; u_k is input vecto; A_k is one-step transfer matrix from t_k to t_{k-1}; B_k is control input matrix; C_k is observation matrix; D_k is the feedback matrix of the observed variable; Γ_k is noise driving matrix; ξ_k is system process noise; η_k is observation noise.The ξ_k and η_k need to be Gaussian white noise which is independent of each other and the mean value is zero, the relation of the ξ_k and η_k is demonstrated as follows:

$$\begin{cases} E[\xi_k] = 0, E\left[\xi_k \xi_k^{\ T}\right] = Q_k \\ E[\eta_k] = 0, E\left[\eta_k \eta_k^{\ T}\right] = R_k \\ E\left[\xi_k \eta_k^{\ T}\right] = 0 \end{cases} \tag{7}$$

where Q_k is the covariance matrix of ξ_k ; R_k is the covariance matrix of η_k.

If the system model is linear, state variable x_k and observation variable y_k satifiy the relation of forluma (5) and (6), process noise ξ_k and observed noise η_k satifiy the forluma (7), the recurrence is as follows.

Initial condition of filter equation is as follows:

$$\hat{x}_{00} = E(x_0), P_{00} = \mathrm{var}(x_0) \tag{8}$$

Status estimation time update is as follows:

$$\hat{x}_{k/k-1} = A_{k-1}\hat{x}_{k-1} + B_{k-1}u_{k-1} \tag{9}$$

Error covariance time update is as follows:

$$P_{k/k-1} = A_{k-1}P_{k-1}A^T{}_{k-1} + \Gamma_{k-1}Q_{k-1}\Gamma^T{}_{k-1} \tag{10}$$

Kalman gain matrix is as follows:

$$K_k = P_{k/k-1}C^T{}_k(C_k P_{k/k-1}C^T{}_k + R_k)^{-1} \tag{11}$$

State estimation observation update is as follows:

$$\hat{x}_k = \hat{x}_{k/k-1} + K_k(y_k - C_k\hat{x}_{k/k-1} - D_k u_k) \tag{12}$$

Error covariance observation update is as follows:

$$P_k = (I - K_k C_k)P_{k/k-1} \tag{13}$$

where y_k is the observed value at the t time and is input by the outside world.

The calculation flow of KF algorithm is shown in Figure 1.

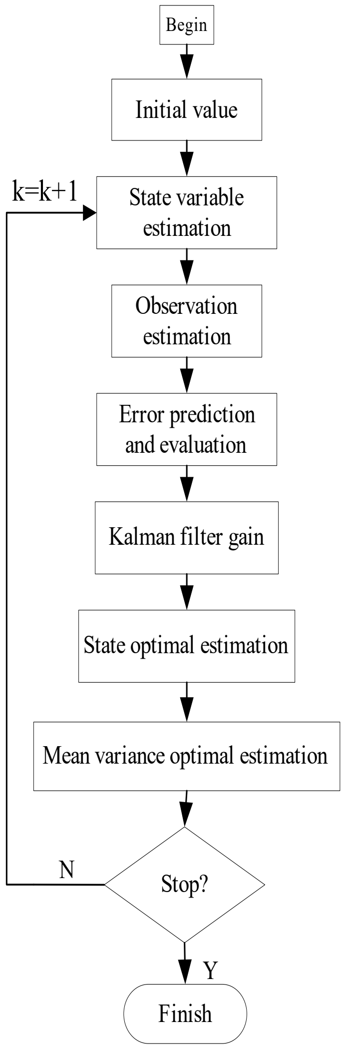

Figure1. Kalman filter flow chart

KF algorithm is based on such a cyclic iterative operation flow, which continuously converges the estimated value to the actual value and reduces the error.

KF algorithm is only applicable to linear model system, and most of them are nonlinear systems in practical engineering. To estimate its state, it is necessary to linearize the nonlinear system, and it is the core idea of extended Kalman Filter(EKF) method.

In SOC estimation, battery can be regarded as a dynamic system, which is composed of input and output, and the state value of the system can be obtained by checking the observed values of the system. The state quantity of the system is a variable that the battery can not collect directly when the vehicle is running in [4], such as SOC value, the observation of the system is the value that can be collected in real time, such as the terminal voltage of the battery. The biggest characteristic of KF algorithm is that it is retroactive. The whole process can be realized in computer without storing a large number of observed data in [5]. This advantage makes KF and its derivative algorithms most popular with scholars at home and abroad in the estimation of SOC of vehicle power batteries, and has become a hot research topic at present.

However, the accuracy of SOC estimation depends to a large extent on the accuracy of battery model. The working characteristics of the power battery are highly nonlinear. There is an error after KF linearization. If the battery model is not accurate, the estimation results are not reliable. KF algorithm is complex, the computation is large, the calculation period is long, and the high hardware performance is required. In order to improve the problem that SOC estimation by EKF algorithm model is not accurate enough, scholars have done a lot of research in this field.

The interaction between heat and electricity in battery is considered, and a new thermoelectric model of the battery is proposed by combining the thermoelectric model with the electronic model. The internal temperature and SOC are estimated in real time by EKF in [6]. On the basis of the second-order RC dynamic model, the EKF and CC methods are combined to estimate the SOC, which provides an effective choice for the running time of the vehicle in [7]. When the system is strongly nonlinear, the accuracy of EKF estimation will be seriously reduced, and even divergence will occur. According to the error of the observation equation, the Kalman gain correction coefficient is added to the original EKF filtering process to overcome the estimation error caused by the inaccurate initial value of SOC, and the SOC estimation error caused by the observation equation error can be further reduced. The relative error of SOC estimation is less than 5% in [8]. In practical problems, it is difficult to find the Jacobian matrix of nonlinear function by using EFK algorithm. Therefore, on the basis of the first order RC model, the grey prediction model (GM) and EKF are combined, and the GM-EKF algorithm is proposed for SOC estimation in [9]. GM (1, 1) is used to replace the Jacobian matrix in EKF algorithm. Compared with EKF algorithm, the error estimation of this method is less than ±0.005, and the algorithm has the ability of real-time online update. On the basis of PNGV model, the adaptive extended Kalman Filter(AEKF) algorithm is used to improve the accuracy of SOC estimation, and the uncertainty of battery model and noise is solved. The effectiveness of the method is verified by a series of simulation tests under UUDS and UDDS conditions. At the same time, the algorithm has better convergence and robustness in [10]. The influence of battery temperature on charge and discharge is considered, resulting in SOC estimation error in [11]. Temperature compensation is introduced into Thevenin model, and the uncented Kalman Filter(UKF) algorithm is used to realize SOC estimation. Under the condition of NEDC, it is compared with the traditional UKF algorithm. The maximum error of SOC is less than 3%. Moreover, the algorithm can converge quickly when the initial SOC error exists. In view of the defects of UKF, the fading factor and attenuation factor are introduced into the filtering gain matrix of the iterative equation by UKF in [12]. The optimization algorithm can adapt to the sudden change or slow change of different battery characteristic parameters with the change of working conditions, and can estimate SOC in real time. It is easy to be engineering. On the basis of the first-order RC model, the AUKF algorithm is used to estimate the SOC in [13]. If the initial value is correct, the error is small. Even if the initial value is incorrect, the algorithm has good convergence and quickly adjusts to the correct orbit. The optimized battery observation model (modeling and compensation of battery relaxation effect and polarization phenomenon) and state model (introducing temperature influence coefficient, equivalent Coulomb efficiency and aging coefficient) are used to construct the estimation model by ASKF algorithm in [14]. This algorithm reduces the complexity of the estimation model used in KF algorithm and improves the observation accuracy of SOC.

The square root unscented Kalman filter(Sqrt-UKF) algorithm is proposed in[15], and compared with CC method, portable fuel gauge and EKF.The Sqrt-UKF method has an absolute root mean square error (RMSE) of 1.42% and an absolute maximum error of 4.96%. The errors are lower than the other three methods. Compared with EKF, it represents 37% and 44% improvement in RMSE and maximum error respectively. Furthermore, the

Sqrt-UKFST method is less sensitive to parameter variation than EKF and it requires 32% less computational requirement than the regular UKF.

Li Jun et al proposed the square root central difference Kalman Filter(Sqrt-CDKF) in [16]. The results show that this algorithm has better convergence than EKF. The second-order Thevenin equivalent circuit of lithium battery is established by Ma Qun of Jilin University. The SOC of battery model is estimated by CDKF algorithm. The results show that the accuracy of CDKF is 1.5% higher than that of EKF in [17].

The SOC obtained from the Sqrt-CDKF method can converge to the true biases much quicker in comparison with the EKF method in [18].

Particle Filter and H-infinity Filter

A temperature composed battery model is established which can be used for SOC estimation at dynamic temperatures in [19].A capacity retention ratio (CRR) aging model is established based on the real history statistical analysis of the running mileage of the battery on an urban bus. A SOC-Particle filter (PF) estimator is proposed to eliminate the drift noise effects and the accuracy and robustness of the proposed method are verified.

The adaptive H infinity filter(AHF)-based estimator is established to estimate the battery states in real time with the highest accuracy and strong robustness among the three filters(AHinf, Hinf, EKF) in [20]. If the initial SOC and SOE are correctly set,the maximum SOC and state of energy(SOE) estimationerrorsare only 0.04% and 0.06% respectively.

The AHF algorithm is used for SOC estimation, and the model parameter identification is carried out off-line for each phase of the charge and discharge of battery, and the estimation result of this algorithm is better than that of the EKF and SRUKF methods in [21].

A multiscale dual H-infinity filter (HIF) is proposed and capacity in real time with dual time scales in response to slow-varying battery parameters and fast-varying battery state in [22]. The results show that the proposed multiscale dual HIFs has better robustness and higher estimation accuracy than the single/multiscale dual KFs. The proposed method can converge to the reference value gradually and be stabilized within 2%.

Sliding Mode Observer Method

Adaptive sliding mode observer is proposed based on fractional equivalent model in [23]. This method can compensate the model error, help to reduce the high frequency chattering and improve the converge speed.

A sliding mode algorithm is adopted to estimate SOC based on a parameter adaptive battery model in [24].The error of SOC estimation is less than 2% under the UDDS driving cycles.

A discrete-time sliding mode observers (DSMO) is adopted based on the Thevenin equivalent model in [25]. The model parameters are identified at different current rate and ambient temperature and the dynamic error is 3% .

Adaptive Artificial Intelligence Algorithm Based on Battery "Black Box Model"

Fuzzy Logic Algorithm

Fuzzy logic algorithm is a control strategy for objects which are difficult to establish accurate mathematical model, which is based on fuzzy reasoning and imitates human thinking mode. A cooperative study between vilkmova University and US Nannocorp Company in the United States shows that using fuzzy logic to estimate

SOC, can obtain efficient and reliable results in [26], and the research by Tsinghua University also shows that it has high accuracy and is easier to obtain through some ways in [27].

The fuzzy control method of off-line calculation and on-line look-up table is proposed by Hunan University in [28]. The residual capacity of power battery is calculated by using the relationship between the voltage at the lower end of constant current discharge and the remaining time. The results show that the maximum error is less than 1%.

A parameter adaptive equivalent circuit model based on multi-input and multiple-output (multiinput multi-output, MIMO) fuzzy-control) is proposed in [29]. The parameters of the model are modified dynamically and in real time by MIMO fuzzy regulator to achieve accurate modeling. The experimental results show that even if SOC is less than 20%, SOC estimation error can still be controlled within 4%.

Neural Network and its Improvement

Neural network algorithm is a new algorithm to simulate the human brain and its neurons to deal with nonlinear systems. It does not need to deeply study the internal structure of battery, but only needs to extract a large number of input and output samples from the target battery in advance, and input it into the system established by this method, run to obtain SOC value. This method can effectively avoid the error caused by the need to linearize the battery model in KF, and can obtain the dynamic parameters of battery in real time. However, the workload of this method is large in the early stage, so it is necessary to extract a large number of comprehensive target samples to train the system. The input training data and training methods greatly affect the estimation accuracy of SOC. By training a large number of historical data for SOC estimation of power batteries, the method has high accuracy and adaptability, and the estimation accuracy mainly depends on the effectiveness of the test data, and the operation quantity is large. It is difficult to realize the cost-controlled electric vehicle processing system.

Neural network is generally divided into three layers: input layer, output layer and hidden layer. Figure 2 shows a three-input and two-output neural network battery model with input parameters of current, SOC, temperature, output voltage and internal resistance.

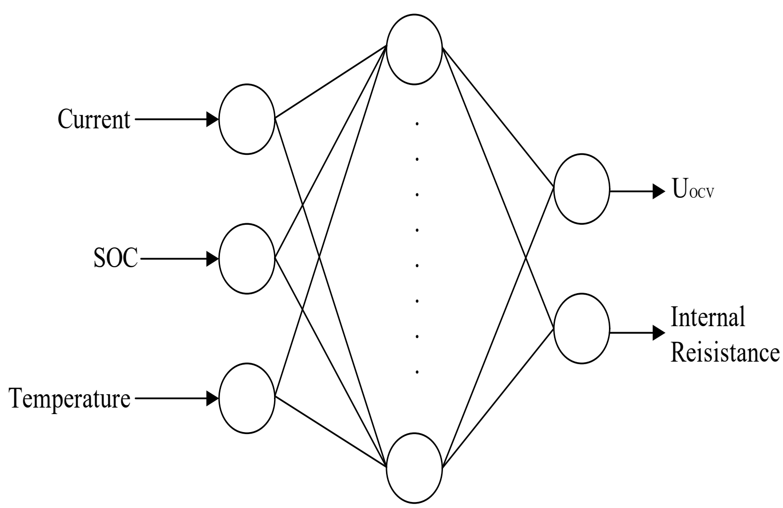

Figure2. *Battery Model based on Neural Network*

After the sample selection, the network is trained, and the training process is shown in Figure 3.

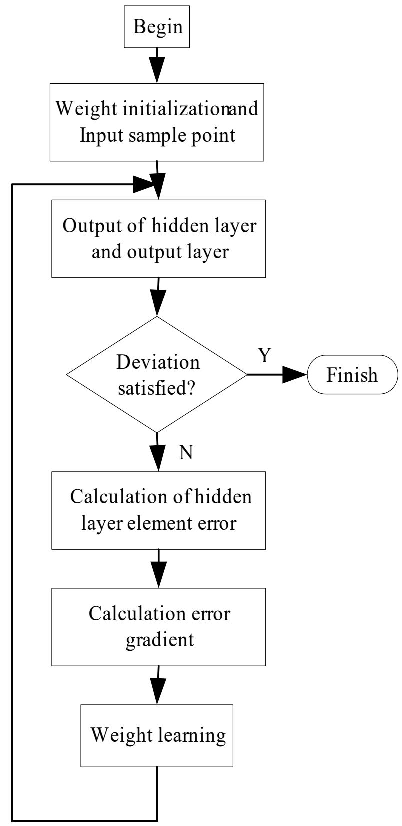

Figure3. *Network training flow chart*

An adaptive neuro-fuzzy inference systems (ANFIS) is proposed estimating SOC of Lithium-ion batteries based on ANFIS modeling of cell characteristics in [30].

Backtracking search algorithm (BSA) is used to improve accuracy of SOC estimation by improving back-propagation neural network (BPNN) capability in [31]. The results show that this method outperforms other neural network with high accuracy under different EV profifiles and temperatures.

A three layer improved BP neural network algorithm is proposed to reduce the SOC prediction error in [32]. The difference between the improved BP neural network SOC estimates and the actual SOC curves is very small.

Other Algorithms

1) Support vector regression method

Support vector regression method(SVR) is based on the principle of structural risk minimizing and minimizing empirical risk and model complexity in [33]. Tsinghua University has used it to estimate SOC, compared with complex neural network algorithms. The research network of Shandong University also shows that the support vector regression algorithm approximates the real value of SOC better than the neural network algorithm.

2) Genetic algorithm

Supervised chaos genetic algorithm(CGA) based on state of charge determination method was proposed in [34]. This method has great performance with less computation complexity and is little influenced by the unknown initial cell state.

Composite Algorithm

Some composite algorithms are used to SOC estimation,such as fuzzy logice KF[35], GA-RBF neural network in [36], AEKF and Wavelet Transform Matrix in [37], PSO-SVM(support vector machine) in [38][39].

Summary

At present, SOC estimation technology used in BMS is not very mature. Although there are many kinds of SOC estimation methods, all kinds of methods have some defects, which are difficult to meet the requirements of SOC real-time online and high precision estimation. In the future, the research of SOC estimation method will be improved from four aspects. First, a rich database is established through a large number of experiments, so that SOC estimation can be based on, there is evidence to be investigated; Secondly, SOC estimation relies on the hardware technology to improve the measurement accuracy of current, voltage and so on, to ensure the accuracy of the basic data used to estimate SOC. Thirdly, an accurate battery model is introduced to characterize the dynamic characteristics of the battery more truly. Finally, by synthesizing various algorithms, different correction methods are introduced into different stages of soc to reduce the error in different states and improve the estimation accuracy.

Acknowledgement

This research was financially supported by the Education Department of Sichuan.

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Citation: Xi-Feng HE, Chang-Jiang DENG, Xing-Mao Liu, "*Review of SOC Estimation Methods for Power Battery". American Research Journal of Computer Science and Information Technology; vol 4, no. 2, 2019; pp: 1-12.*