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New Energy Vehicle Power Lithium Battery Model Establishment Method and SOC Estimation Research

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Abstract: As the main source of power for pure electric vehicles, new energy vehicle power lithium batteries are also a key technology that restricts the development of pure electric vehicles, and can directly affect the driving performance of vehicles. A reliable and efficient management system (Battery Management System, BMS) can allow the lithium-ion battery to output its best performance stably, while ensuring that the battery has a long enough service life. State of charge (SOC) estimation plays an important role in Li-ion battery management systems. The establishment of the battery working model is an important part of the state of charge estimation. Therefore, higher requirements are put forward for the establishment of the battery model. At the same time, the error of the subsequent data processing and estimation results is smaller, and the Kalman filter is often used for processing. This paper starts from the current situation of model research and improvement, focuses on the equivalent circuit model, analyzes the advantages and disadvantages of each model, and summarizes the comparative research on the analysis and processing effect of Kalman filter. And further experiment verification of SOC estimation through battery test experiments and algorithms, use Thevenin model, use least squares method for parameter identification, and finally use Kalman filter for SOC estimation, according to the analysis of the results, the fitting accuracy is 1.69%, provided by battery research a strong theoretical foundation.

Keywords: Battery Management System; Equivalent Circuit Model; Parameter Identification; Kalman Filter; SOC.

1. Introduction

With the increasingly serious environmental pollution and fuel energy problems, as well as the increasing demand for energy saving and emission reduction [1], lithium-ion batteries are used as the power source of electric vehicles. In order to monitor the working status of the battery in real time, to ensure the safety, reliability and durability of the battery performance, an excellent battery management system (BMS) is indispensable [2]. Tsinghua University LU [3] et al. reviewed the key technical problems in the management of lithium-ion batteries for electric vehicles. However, the existing BMS design is relatively conservative and cannot fully utilize the battery state of power (SOP) of the battery pack in practical applications. Therefore, a method for estimating the peak power of a dynamic battery model based on multiple constraints is proposed. The key parameters that can provide or return the peak capacity of electric energy in a short period of time further guarantee the safety of the battery during use and prolong the service life of the battery. SOC is one of the core parameters of the battery and is crucial to the BMS. Therefore, in order to develop an optimal BMS for electric vehicles, it is necessary to find a method that can accurately estimate the battery SOC. Common SOC estimation methods can be divided into three types: open-loop methods, data-driven methods, and model-based methods. The open-loop method includes the ampere-hour integration method and the OCV method. The ampere-hour integration method has the difficulty of eliminating the accumulated error during the integration process in the application process. The OCV method is not suitable for online estimation because it takes a long time to restore the terminal voltage to OCV; data-driven methods usually include neural network methods, fuzzy logic methods, and support vector machine methods, all of which require large amounts of training data and complex calculations to establish the relationship between SOC and directly measurable parameters such as voltage and resistance. The nonlinear relationship; the model-based SOC estimation method is to estimate the SOC by combining the battery model and some filtering algorithms, which is the most commonly used method.

2. Battery Composition and Battery Model

Lithium-ion battery is a common rechargeable battery. It is composed of multiple components, each of which has different structures and functions. The performance of the power battery of a new energy vehicle directly affects the fuel safety and stability of the driving car. The battery is mainly composed of positive electrode, negative electrode, electrolyte and separator. Among them, the positive electrode is an important part of lithium-ion batteries, usually composed of lithium compounds, such as cobalt oxide, nickel oxide, lithium iron phosphate, etc. The main job of the positive electrode is to accept lithium ions, intercalate or release lithium ions during charging and discharging, generate electrochemical reactions, and provide current output. The negative electrode is another key component. Graphite is often used as the negative electrode material, which has the ability to intercalate or delithiate lithium, and can absorb or release lithium ions. During the charging and discharging process, the negative electrode receives lithium ions from the positive electrode, intercalates lithium during charging, and delithiates during discharging. The electrolyte is the medium between the positive and negative electrodes, usually liquid or solid. Liquid electrolytes often use electrolytes composed of organic solvents and lithium salts, while solid electrolytes use solid materials with ion conductivity. The role of the electrolyte is to provide an ion-

conducting path that enables lithium ions to move between the positive and negative electrodes. The diaphragm is located between the positive and negative poles, which plays the role of isolation and prevents the two poles from being directly short-circuited. Separators are usually made of polymer materials that have good ion conductivity while preventing direct contact with the battery's internal components. When the battery is in a conductive state, the movement of lithium ions promotes the chemical reaction on the two electrodes to realize the conversion of chemical energy and electrical energy.

When studying the state of charge of the battery, due to the internal undetectability of the battery, it is necessary to establish a model to indirectly study the internal characteristics of the battery. Therefore, it is first necessary to establish a battery model, and its accuracy directly affects the accuracy and performance of battery SOC estimation. Battery models mainly include electrochemical models, neural network models, and equivalent circuit models. Among them, the electrochemical model is usually more accurate than the latter when simulating the state of the battery, and the simulation effect is more complete, but it is not easy to operate. In contrast, the equivalent circuit model has the advantages of good performance, easy operation, and high precision, and can observe the dynamic characteristics of each monomer. Therefore, it is considered as one of the most suitable models for SOC estimation [4]. The equivalent circuit model needs certain data to train the model to achieve the validity and robustness of the model. Physical components such as capacitors and resistors are commonly used in equivalent circuits to describe the working characteristics of batteries. Thus, an equivalent circuit model is formed, which can effectively represent the internal reaction of the battery.

Common equivalent models include Rint model, Thevenin model, PNGV model, GNL model, etc.

The Rint model is also called the internal resistance model, and it is the simplest equivalent circuit model. As shown in Figure 1, the calculation amount of the model is small and the speed is fast. Complicated nonlinear calculations are not required, and calculation efficiency can be improved during simulation. However, the model is relatively inaccurate in describing some nonlinear components, especially in the case of drastic changes in nonlinear behavior, the model may not be able to obtain nonlinear characteristics.

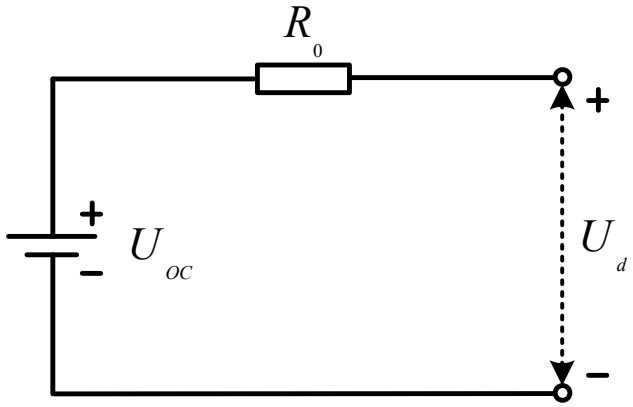


Figure 1. Rint model

The Thevenin model is also called the first-order RC model, which is based on the Rint model and connects an RC loop in series. As shown in Figure 2, by abstracting the circuit as a combination of power supply and resistance, it is easier to conduct circuit analysis and design, and the accuracy of the model is improved, but the applicability of the model in nonlinear systems and high-precision circuits and with limited accuracy. In practical applications, it is necessary to evaluate the applicability of the Thevenin model according to specific circuit types and analysis requirements.

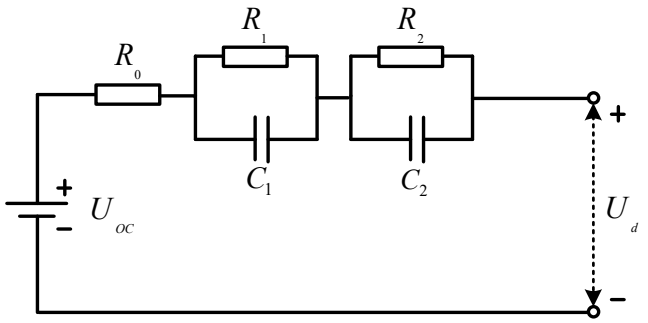


Figure 2. Thevenin model

The PNGV model connects a capacitor in series on the basis of the Thevenin model, as shown in Figure 3. This model can well describe the output characteristics of the battery, but the series capacitor will increase the cumulative error. But the model accuracy depends on the correct extraction of parameters. Obtaining accurate parameters requires experimental measurements or the use of specific parameter extraction methods, which will not only cause additional experimental equipment and time, but also cause large errors due to current accumulation, which is not conducive to long-term simulation.

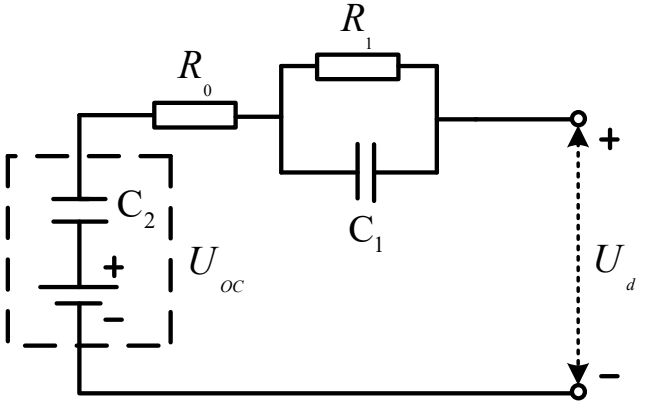


Figure 3. PNGV model

The GNL model has high flexibility and can be adjusted and customized according to specific situations. As shown in Figure 4. The model can adjust the parameters of the model according to the actual characteristics and working conditions of the components to improve the accuracy and applicability of the model. However, compared with the linear model, this model has a large amount of calculation, especially in complex circuits containing a large number of nonlinear components. Moreover, the complex topological structure and difficult-to-identify parameters of the model make it difficult to apply in actual engineering.

On the basis of the original model, Changhe L [5] improved the equivalent circuit model on the second-order basis and created a fractional-order equivalent circuit model. Internal reaction process.

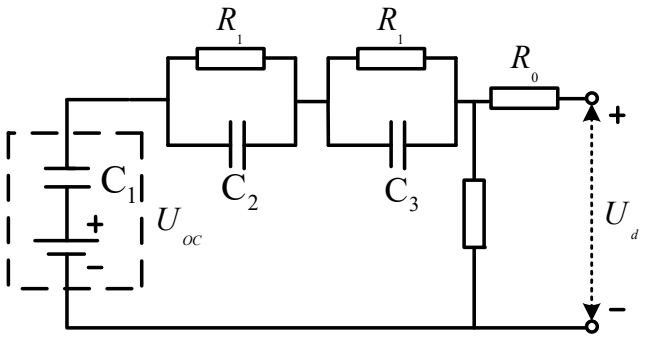


Figure 4. GNL model

3. Battery Model Parameter Identification

Parameter identification plays an important role in battery SOC estimation. Parameter identification refers to determining the parameter values in the battery model through experiments or data analysis methods, so that the model can more accurately describe the behavior of the battery.

The SOC estimation of a battery needs to reflect the actual state of charge of the battery as accurately as possible. Through parameter identification, more accurate battery models and parameter values can be obtained, and the accuracy of SOC estimation can be improved. Accurate SOC estimation helps to know the remaining power of the battery more accurately, provides accurate information for the operation and control of the battery system, helps to optimize the battery usage strategy and the control algorithm of the battery management system, and then can improve the performance of the battery management system, extend battery life, and contribute to the development of sustainable energy systems.

Common methods for model parameter identification include particle swarm algorithm, least squares method, genetic algorithm, neural network algorithm, etc.

Particle Swarm Optimization (PSO) [6] has the advantages of less adjustment parameters, fast convergence speed, and easy implementation. In this algorithm, candidate solutions are regarded as particles, and the optimal solution is searched by iteratively updating the velocity and position of particles. In battery parameter identification, particle swarm optimization algorithm can be used to search the parameter space to find the optimal parameter combination. By defining a fitness function that measures the difference between the model output and actual observations, the PSO algorithm can iteratively adjust parameters to gradually optimize the quality of the model fit.

The least squares method [7] is a common mathematical optimization technique, which obtains the estimated value of the system parameters by minimizing the sum of squares of the error between the observed data and the estimated value. In the parameter identification of the equivalent circuit model, the least square method can be used to fit the error between the predicted value of the model and the actual observed value. Find the optimal combination of parameters so that the model can best fit the actual data.

Genetic algorithm [8] is a heuristic optimization algorithm that simulates the natural selection and genetic mechanism in biological evolution. Can be used to search the parameter space to find the optimal solution. In the parameter identification of the equivalent circuit model, the algorithm can be used to optimize the parameter combination. By defining the fitness function to evaluate the pros and cons of parameter combinations, and generate new parameter combinations through selection, crossover and mutation operations, and gradually search for the optimal solution.

The neural network algorithm [9] is a mathematical model that simulates the biological neural network. It has a strong fitting ability and can be applied to the parameter identification of the equivalent circuit model. In parameter identification, neural network algorithms can be used to establish nonlinear relationship models, optimize parameters, improve robustness and generalization capabilities, and adapt to complex battery behaviors. Compared with the traditional parametric model, the neural network algorithm is a non-parametric model with greater flexibility and adaptability, which can more accurately fit battery data and provide accurate parameter estimation.

4. Battery SOC Estimation Algorithm

After the battery model is established, it is more important for parameter calculation and data analysis. Kalman filter is an efficient optimal estimator and a commonly used battery SOC estimation algorithm. It uses recursive calculation to estimate SOC. This algorithm It can simulate and calculate the nonlinear state of the battery very well. At the same time, noise interference in the test data can be reduced.

The Kalman filter (KF) is considered to be one of the most widely used model-based methods due to its excellent online calculation and self-correction capabilities. But the OCV-SOC relationship of the battery is nonlinear, resulting in a nonlinear spatial state of the battery system, so the basic Kalman filter cannot be used to solve this problem.

In order to solve the nonlinear problem, Z.Chen[10] proposed a SOC estimation method based on 2-RC model Kalman filter. The battery has nonlinear characteristics, and the extended Kalman filter (EKF) can achieve higher accuracy.

In addition, R.xiong[11] and others proposed a data-driven multi-scale extended Kalman filter algorithm to achieve dual estimation of battery parameters and states. But there are also new problems, EKF will increase the estimation error in strong nonlinear systems. In order to improve the estimation accuracy, L. Yang [12] proposed an improved UKF method to solve the problem that depends on the exact model and prior noise statistics. F.Xie [13] proposed the combination of support vector machine and UKF to estimate SOC, and combined the decomposition and calculation process to improve the stability of the UKF algorithm. After precise experiments, this method can reduce the error by 1%. Fangfang Yang [14] used an unscented Kalman filter (UKF) to filter out noise and further reduce the estimation error. The method is evaluated using data collected from the Dynamic Stress Test, the Federal Urban Driving Schedule, and the US06 test. Experimental results show that this method can well control the influence of ambient temperature and estimate the battery SOC at varying temperatures from 0°C to 50°C.

Xinyou Lin[15] proposed an SOC estimation method based on an accurate equivalent circuit model based on an adaptive unscented Kalman filter (AUKF). By updating the system noise covariance and measurement noise covariance in real time, the algorithm Estimation of state variables is more efficient and accurate. But there are also shortcomings. This method increases the complexity of the battery model.

S.Wang [16] developed an improved particle-reduced adaptive Kalman filter, which aims to eliminate redundant information and abnormal information to improve the accuracy of SOC estimation. H.Pan[17] et al. proposed a gray extended Kalman filter based on a new OCV model of cubic-Hermitian interpolation, and combined the EKF algorithm with the covariance matching method. However, due to various external factors, experiments have proved that there may be inconsistencies in SOC estimation.

5. Battery SOC Estimation Experiment Verification

This paper conducts experimental verification of the model and algorithm based on the review content, and uses the Thevenin model to estimate the battery SOC online. The model verification results are shown in Figure 5. It can be seen from the figure that the fitting effect of the model is good, and it can be used for further verification in subsequent experiments.

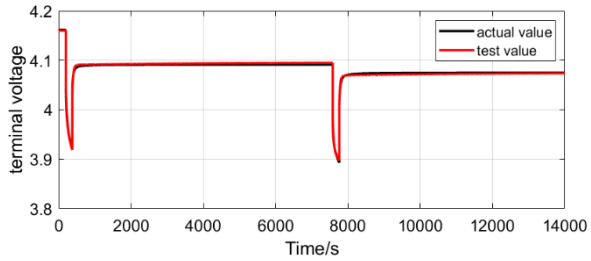


Figure 5. Comparison between real value and test value

Compared with the particle swarm algorithm, genetic algorithm and neural network algorithm, the mathematical derivation of the least squares algorithm is relatively simple and easy to understand. The parameter estimation can be obtained directly by minimizing the residual sum of squares, without complex optimization process or neural network training, and the parameter estimation obtained by the least square method has physical interpretation, and can directly correspond to the physical quantity of the internal characteristics of the battery. This helps researchers understand how batteries work and what factors affect them. Therefore, this paper uses the least squares method for parameter identification. The calculation results are shown in Table 1 below.

Table 1. Parameter identification results

parameter name	Calculated
C_1	1.4427e+04
C_2	1.0914e+06
R_0	0.0039
R_1	0.0019
R_2	0.0033

Kalman filter is a commonly used battery SOC estimation algorithm, which is calculated by recursive calculation. In this paper, Kalman filter is used to estimate battery SOC online. The experimental data is tested by Xinwei battery test system. The working condition data is set in the computer equipment as the battery input working condition, and the U.S. urban cycle working condition (UDDS) is used as the test working condition to collect various data of the battery.

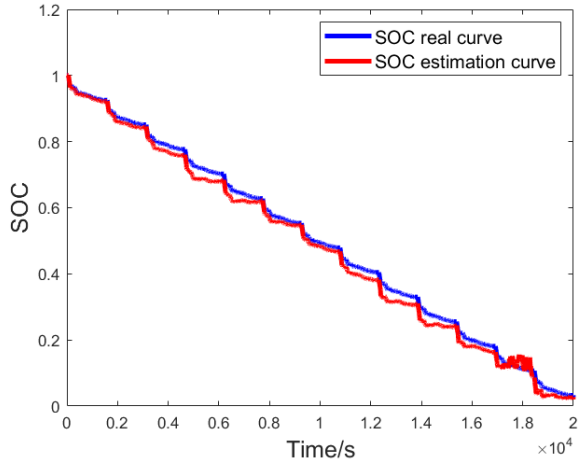


Figure 6. Comparison of SOC estimated value and real value

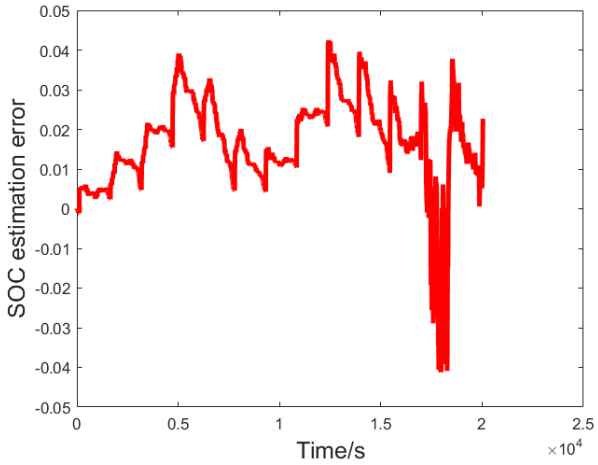


Figure 7. SOC estimation error curve

The battery SOC estimation effect is shown in the figure. The actual value and the estimated value are almost the same, and the fitting accuracy is 1.69%. Battery research provides a strong theoretical basis. This highly accurate fitting ability enables us to predict and evaluate more accurately Battery performance and characteristics.

6. Conclusion

This paper first briefly describes the composition and working principle of the battery in the battery management system, emphasizing the importance of battery state of charge estimation in the field of new energy vehicles. Secondly, the article gives an overview of the common types of battery models, and also analyzes the algorithm for parameter identification of battery models. Then, the article summarizes the research status of the Kalman filter algorithm currently used in the field of battery SOC estimation and its improvement. Finally, in order to verify the feasibility of the proposed SOC estimation scheme, the actual battery test data proves that the proposed scheme has high accuracy and reliability in battery SOC estimation.

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