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Real-Time Online Estimation Technology and Implementation of State of Charge State of Uncrewed Aerial Vehicle Lithium Battery

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Abstract: The *SOC* estimation of UAV lithium batteries plays a crucial role in the mission planning and safe flight of UAVs. Aiming at existing UAV lithium battery *SOC* estimation problems, such as low estimation accuracy and poor real-time performance, a real-time online estimation scheme for UAV lithium battery *SOC* is proposed. A model-based approach is adopted to establish an *SOC* estimation model on the basis of the Thevenin equivalent circuit model, and a UAV lithium battery online monitoring device is developed to monitor the current and voltage of the UAV lithium battery in real time and import the data into the *SOC* estimation model in real time for calculation. Using the developed online monitoring device, the current and voltage of the lithium UAV battery are monitored in real time, and the data are imported into the *SOC* estimation model in real time for calculation, realizing the real-time online estimation of the *SOC* of the lithium UAV battery. The experimental results show that the program can realize the real-time online estimation of UAV lithium battery *SOC*, and the estimation error is less than 3%, which meets the requirements of online estimation accuracy of the UAV lithium battery *SOC*.

Keywords: UAV lithium battery; *SOC*; model-based approach; Thevenin model; online estimation

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1. Introduction

Uncrewed Aerial Vehicles (UAVs), specifically the kind of uncrewed aerial vehicle that flies remotely or autonomously, has been widely used in many fields, such as military reconnaissance, aerial photography, agricultural plant protection, and logistics and distribution [1,2]. The wide application of UAVs has put forward higher requirements for battery technology, in which Li-ion batteries have become the preferred power source for UAVs by ensuring higher safety while having advantages such as low weight and high discharge [3]. The real-time online estimation of the *SOC* of Li-ion batteries for UAVs plays a crucial role in the control and safe flight of UAVs [4]. However, the *SOC* of Li-ion batteries cannot be measured directly and needs to be obtained indirectly via other parameters and methods. Since the relationship between the voltage, current, internal resistance, and other parameters of Li-ion batteries exhibits a high degree of nonlinearity, it makes the accurate estimation of *SOC* difficult [5]. Currently, small UAV *SOC* estimation commonly uses the voltage measurement method and ampere-time integration method to estimate battery *SOC*; the estimation accuracy is within 10%, and the estimation technique has problems such as low estimation accuracy and poor real-time performance [6].

Therefore, this paper will address the problem of real-time online estimation of UAV lithium battery *SOC*. Using a model-based approach, a real-time online estimation scheme for UAV lithium battery *SOC* is proposed, and a lithium battery *SOC* estimation model is established on the basis of the Thevenin equivalent circuit model, real-time monitoring of the current and voltage of the UAV lithium battery, and real-time importing of the data into the *SOC* estimation model, realizing real-time estimation of the *SOC* of the UAV lithium battery, and verifying the scheme via experiments.

2. Methods

SOC (State of charge) refers to the percentage of the remaining capacity of the battery to the total capacity, which is used to reflect the remaining capacity of the battery [7]. The estimation of *SOC* is an important part of the UAV battery management system, and the accuracy of the estimation directly affects the flight performance and endurance of the UAV [4]. *SOC* is numerically defined as the ratio of the remaining capacity of the battery to the capacity of the battery as follows:

$$SOC = \frac{Q_c}{C_I} \tag{1}$$

where Q_c is the remaining capacity of the battery, and C_I is the amount of power that the battery has when it is discharged at a constant current I.

If the *SOC* value is calculated in terms of the amount of electricity discharged, Q, the definition can be expressed as

$$SOC = 1 - \frac{Q}{C_I} \tag{2}$$

where $SOC = 1$ indicates that the battery is fully charged and when $SOC = 0$, the battery is in the state of full discharge.

The *SOC* estimation methods for UAV Li-ion batteries mainly include the open-circuit voltage method [8,9], the amperage-time integration method [10–12], the model-based method [13,14], and the data-driven method [15–18]. The open-circuit voltage method utilizes the fitting relationship between the open-circuit voltage value and the *SOC* to estimate the *SOC*, which belongs to the open-loop estimation method with high estimation accuracy, but because the open-circuit voltage value of the lithium-ion battery needs to be statically acquired over a long period of time, the real-time nature of this method is poor, and it cannot be applied to the estimation of *SOC* under the actual UAV working condition state. The amperage-time integration method also belongs to the open-loop *SOC* estimation method by integrating the discharge current to estimate the *SOC* of the UAV. The amperage-time integration method is also an open-loop *SOC* estimation method, which estimates the *SOC* of Li-ion batteries by integrating the discharge current. This method is easily affected by the accuracy of the current measurement, and the estimation results will generate cumulative errors over time, and at the same time, the method ignores the nonlinearity of the batteries and the influence of the battery temperature on the estimation of *SOC*, which results in low accuracy. The data-driven method is a method of estimating the *SOC* by analyzing the historical data of the batteries, and the internal chemical reaction, temperature change, and battery degradation of the batteries are taken into consideration. The data-driven method is a method to estimate *SOC* by analyzing the historical data of the battery, and this method takes into account the effects of the internal chemical reaction, temperature change, battery degradation, etc., on *SOC*, ~~so the accuracy of this method is lower.~~ and has a higher accuracy, but the method requires higher data accuracy and quality, and if there are a large number of errors and missing data, it will lead to a significant reduction in the accuracy of the *SOC* estimation, and the computational cost is high, which makes it difficult to be applied to the actual estimation of the *SOC* of lithium batteries for UAVs; the model-based method is a method for estimating battery *SOC* by establishing a battery equivalent model, which takes into account the effects of internal chemical reactions, battery temperature and other factors, and is less data-dependent than the da-ta-driven method. The method can adjust the parameters according to the characteristics of the battery to adapt to different models of lithium batteries, and at the same time, it has the advantages of high accuracy, good real-time performance, and strong robustness [19]. Considering the flight requirements of UAVs, the existing technical conditions and the characteristics of lithium batteries, the model-based method is chosen to estimate the *SOC* of UAV lithium batteries, which consists of two parts: model building and state estimation algorithm, firstly, it is necessary to build the model and identify the parameters of the model, and then the design and validation of the *SOC* estimation algorithm is carried out.

This paper proposes a scheme for the real-time estimation of UAV lithium battery *SOC* using a model-based method, as shown in Figure 1. First, the MATLAB/Simulink R2022b software is used to establish a UAV lithium battery equivalent circuit model, and an offline parameter identification method is used to identify the internal parameters of the model and perform simulation verification. Then, the *SOC* estimation model of UAV lithium battery is established according to the battery equivalent circuit model, and the online monitoring module of UAV lithium battery status is designed and developed. The monitoring module measures and collects the real-time voltage and current of the lithium battery and transmits the data to the control terminal, imports the data into the *SOC* estimation model, and then realizes the real-time online estimation of *SOC* via the calculation of the *SOC* estimation model.

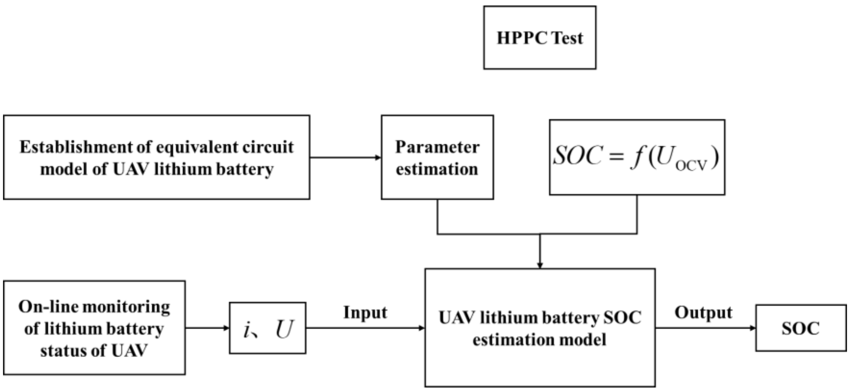

Figure 1. Real-time online estimation scheme of UAV lithium battery *SOC*.

3. Modeling and Parameter Identification

The battery equivalence model is a mathematical model used to describe the behavior of the battery and is often used to simulate and predict the state parameters of the battery under different operating conditions, such as *SOC* and SOH (State of Health). The accuracy of the model is a key factor affecting the accuracy of *SOC* estimation [20].

3.1. Equivalent Modeling of Lithium Drone Batteries

Battery models mainly include electrochemical models, equivalent circuit models, and neural network models. The electrochemical model has advantages in battery electrode concentration estimation and charging strategy optimization due to its consideration of the internal characteristics of the battery. However, due to the high complexity of the model and a large amount of calculation, there are certain limitations in the practical application of the neural network model, and the neural network model obtains the prediction data, such as battery *SOC*, via the input of the collected battery information, such as current, voltage and temperature. The model requires a large amount of data and computing resources to train the model, and the estimation accuracy is highly dependent on data and the convergence speed is slow, which is not suitable for real-time online estimation of UAV lithium battery *SOC*. The equivalent circuit model uses electrical components such as resistors, capacitors, and voltage sources to form equivalent circuits to simulate the dynamic characteristics of a battery. The model is easy to implement and widely used for analysis using circuits and mathematical methods.

Lithium battery equivalent circuit models mainly include the Rint model [21-23], the Thevenin model [24-26], the dual-polarization model [27,28], the PNGV model [29], the GNL model [30], etc. The Rint model, also known as the internal resistance model, consists of an ideal voltage source U_{OCV} and an ohmic internal resistance R_0. U_{OCV} and R_0 are both a function of the *SOC* and the temperature and is a simple and easy-to-implement model, but does not take into account the battery polarization effect, and the scope of application is smaller. The Thevenin model adds an RC network to the circuit of the Rint model to take into account the battery charging effect, which can better simulate the battery charging and charging. This model is simple and easy to realize, but it does not consider the polarization effect of the battery, and the scope of application is small. The Thevenin model adds an RC network on the circuit of the Rint model to consider the polarization effect of the battery, and it can better simulate the transient and steady-state characteristics of the voltage and current in the process of charging and discharging of the battery. The dual-polarization model, also known as the second-order RC model, is connected to an RC network in series with the Thevenin model, and the structure is changed to be more complicated. The dual-polarization model, also known as the second-order RC model, is based on Thevenin's model with a series connection of an RC network, which makes the structure more complex but provides a more accurate description of the battery polarization characteristics and can more accurately simulate the actual characteristics of the battery, but the increase in the RC network leads to an increase in the amount of computation; the PNGV model is based on Thevenin's model, with a capacitor C_{b} connected in series with the main line, and the capacitor C_{b} is used to describe the change in the OCV of the battery with the time integration of the load current. The time accumulation of load current on OCV, i.e., the effect of *SOC* changes on OCV, and the estimation accuracy is higher. The GNL model adds capacitance C_{b} and self-discharge resistance R_{s} on the basis of the dual-polarization model, which takes into account both the effect of *SOC* changes on OCV of the power battery and self-discharge phenomenon of the battery, and it is the most accurate of the five equivalent circuit models, but it also has the most complicated structure and a high computational cost, so the model has poor applicability in power battery *SOC* estimation. Among them, the Thevenin model, shown in Figure 2, has a simple structure and also takes into account the dynamic characteristics of the battery, with higher accuracy and lower computational complexity, and is widely used in lithium battery *SOC* estimation [20].

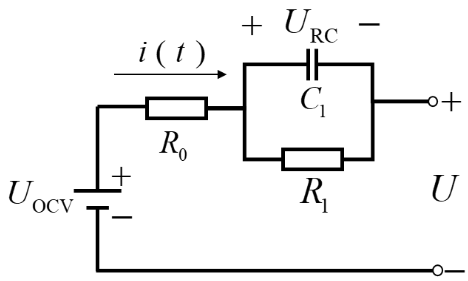

Figure 2. Thevenin equivalent circuit model.

In the figure, U_{OCV} is the electromotive force, R_0 is the ohmic internal resistance, R_1 is the polarization resistance, C_1 is the polarization capacitance, U_{RC} is the RC loop voltage, U is the terminal voltage, and $i(t)$ is the current.

The schematic diagram of the Thevenin equivalent circuit model lists the equations of state for the model as follows:

$$U = U_{\mathrm{OCV}} - i(t)R_0 - U_{\mathrm{RC}} \tag{3}$$

$$\frac{dU_{\mathrm{RC}}}{dt} = \frac{i(t)}{C_1} - \frac{U_{\mathrm{RC}}}{R_1C_1} \tag{4}$$

Based on the Thevenin equivalent circuit model, the equivalent circuit model of the UAV lithium battery shown in Figure 3 is constructed using the Simscape control library in MATLAB/Simulink R2022b software. The model mainly includes the SOC_1 calculation module and the equivalent circuit module. The SOC_1 calculation module is designed based on the ampere-time integration method; the module inputs the initial open-circuit voltage, and after the function, according to the fitting relationship between the open-circuit voltage and the *SOC*, we can obtain the initial *SOC* of the battery. It inputs the battery discharge current, and after the SOC_1 calculation module, calculates the output of the SOC_1. According to the SOC_1, the output of the SOC_1 can be obtained via the parameters of the SOC_1. According to SOC_1, the internal parameter values of the model in the *SOC* state can be obtained by checking the table, which reflects the battery characteristics of the lithium battery in the *SOC* state.

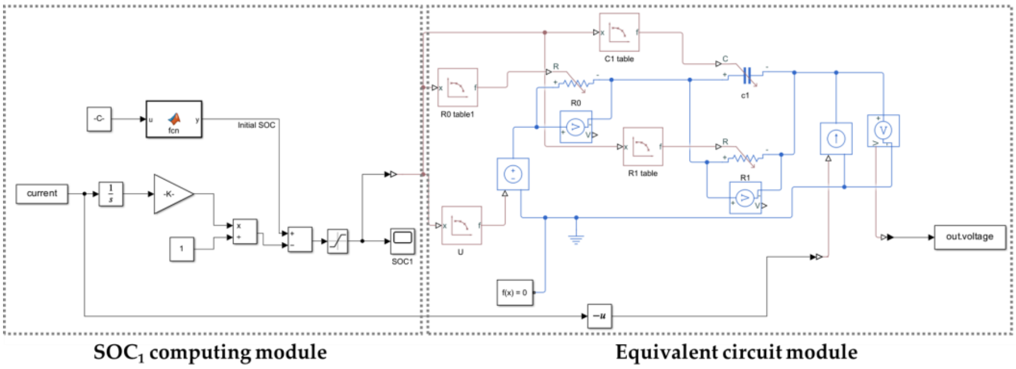

Figure 3. Equivalent circuit model of lithium battery for drones.

3.2. Parameter Identification and Simulation Verification of UAV Lithium Battery

Model parameter identification is the process of analyzing the selected model parameters and determining the specific parameters, and the accuracy of the parameter identification results is the key factor affecting the simulation accuracy of the model. According to the selected Thevenin equivalent circuit model and its equation of state (3~4), the parameters that need to be identified are battery electromotive force U_{ocv}, ohmic internal resistance R_0, polarization resistance R_1, and polarization capacitance C_1. Via the Hybrid Pulse Power Characteristic (HPPC) test of lithium battery, the current and voltage data of the lithium battery are collected, and the electromotive force U_{ocv}, ohmic internal resistance R_0, polarization resistance R_1, and polarization capacitance C_1 of the battery in the equivalent model are identified according to their change law.

Taking the polymer lithium battery as the experimental object, the basic performance parameters of the battery used in the experiment are shown in Table 1.

Table 1. Performance parameters of experimental lithium batteries.

Parameter	Value
Nominal capacity	1000 mAh
Nominal voltage	3.7 V
Charge cut-off voltage	4.2 V
Discharge cut-off voltage	2.75 V
Standard charging	0.5 C

In order to improve the accuracy of the test results, improvements were made on the basis of the traditional HPPC test method [31], which was improved from a constant current pulse test for every 10% discharge of the battery to a constant current pulse test for every 5% discharge. The specific experimental steps are as follows:

(1). Under the set temperature conditions, charge the battery with a constant current and voltage at a charging current of 0.5 C, with a charging cut-off current of 0.01 C, at which time the *SOC* is 100%, and leave it for 1 h.
(2). Discharge 5% of the battery at a discharge current of 1 C and leave it for 1 h.
(3). Discharge the battery with a 3 C pulse current for 10 s and leave it for 40 s; charge it for 10 s and leave it for 40 s (to complete one HPPC experiment).
(4). Perform cyclic experiments on steps (2)-(3) until the *SOC* of the battery = 0%.

In order to obtain the battery characteristics of Li-ion batteries under different temperatures, HPPC tests were conducted at −5 °C, 20 °C, and 40 °C, and the test platform included Sunway BTS–5V6A and thermostat box.

A complete HPPC test current and voltage variation curve is shown in Figure 4. In order to identify the battery parameters in each *SOC* state, the single constant current pulse test current and voltage variation curve are enlarged to study, as shown in Figure 5. The figure stipulates that the charging current is positive, and the discharge current is negative. The A~B stage is the pulse discharge process, and the B~D stage is the static process.

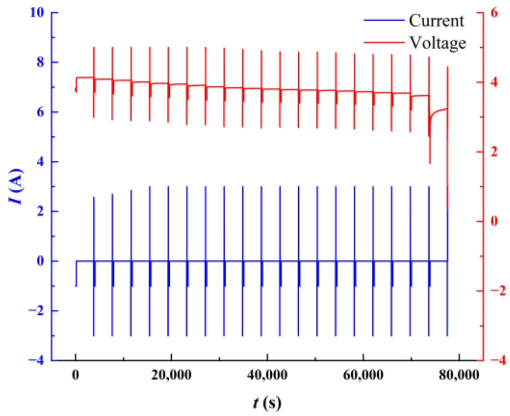

Figure 4. HPPC test current and voltage curve.

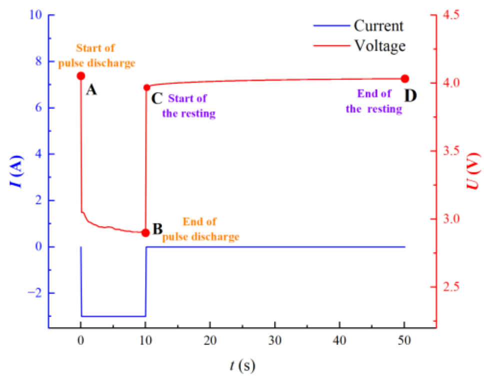

Figure 5. Curve of current and voltage variation for a single constant current pulse test.

The sudden change in the terminal voltage in the B~C stage is caused by the ohmic internal resistance of the battery, and the formula for calculating the ohmic internal resistance is

$$R_0 = \frac{U_{\mathrm{BC}}}{I} \tag{5}$$

The slow rise of terminal voltage in the C~D stage is mainly affected by the polarization resistance and polarization capacitance present inside the battery. In this process, the Thevenin equivalent circuit has zero input response, and the working voltage of the battery at any time in the C~D stage is calculated as follows:

$$U = U_{\mathrm{OCV}} - IR_1 e^{-\frac{t}{\tau}} \tag{6}$$

The first-order exponential function fitting is performed on the rebound voltage curve in the C~D stage, and the fitting equation is as follows:

$$f(x) = \mathrm{A} - \mathrm{B}e^{-ax} \tag{7}$$

Combined with (6) and (7), the calculation formulas of polarization resistance and polarization capacitance can be obtained:

$$\begin{cases} R_1 = \dfrac{\mathrm{B}}{I} \\ C_1 = \dfrac{I}{\mathrm{aB}} \end{cases} \tag{8}$$

Therefore, via the above identification methods, the ohmic internal resistance R_0, polarization resistance R_1, and polarization capacitance C_1 of the battery in different *SOC* states can be obtained, and the identification results are shown in Table 2.

Table 2. Parameter identification results.

***SOC* (%)**	R_0 **(Ω)**	R_1 **(Ω)**	C_1 **(F)**
0	0.303	0.067	150.376
5	0.298	0.043	235.110
10	0.296	0.039	255.537
15	0.286	0.050	202.020
20	0.297	0.036	279.851
25	0.285	0.050	201.613
30	0.295	0.032	309.598
35	0.289	0.043	232.378
40	0.298	0.032	310.559
45	0.301	0.029	347.625
50	0.294	0.036	277.008
55	0.294	0.031	322.234
60	0.290	0.035	288.184
65	0.296	0.034	295.567
70	0.290	0.038	261.552
75	0.296	0.036	280.899
80	0.287	0.046	217.077
85	0.297	0.040	252.738
90	0.289	0.042	239.044
95	0.290	0.042	236.967

According to Kirchhoff's law, the mathematical expression for the electromotive force U_{OCV} in this model can be obtained as follows:

$$U_{\mathrm{OCV}} = U + i(t)(R_0 + R_1) - i(t)R_1 e^{-\frac{t}{R_1 C_1}} \tag{9}$$

Ignoring the influence of the thermodynamic characteristics of the positive and negative electrodes of lithium batteries, the electromotive force is numerically equal to the open-circuit voltage of the battery during the experimental test and analysis. The open-circuit voltage refers to the potential difference between the positive and negative electrodes when the battery passes through without current, that is, the voltage between the positive and negative electrodes when the battery is not working. The electromotive force U_{OCV} of the battery in each *SOC* state under different temperature conditions can be obtained by the HPPC experiment, as shown in Figure 6.

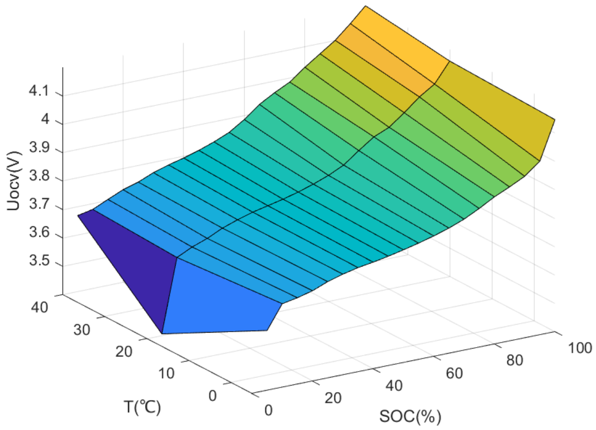

Figure 6. Battery electromotive force at different temperatures and *SOC*.

The Gaussian fitting method with high goodness of fit was selected to fit the U_{OCV}, *SOC*, and the U_{OCV}–*SOC* fitting equation was as follows:

$$\begin{aligned} f(x) &= a_1 \times exp\left(-(\frac{x-b_1}{c_1})^2\right) + a_2 \times exp\left(-(\frac{x-b_2}{c_2})^2\right) + a_3 \times exp\left(-(\frac{x-b_3}{c_3})^2\right) \\ &+ a_4 \times exp\left(-(\frac{x-b_4}{c_4})^2\right) + a_5 \times exp\left(-(\frac{x-b_5}{c_5})^2\right) \end{aligned} \tag{10}$$

Among them, x stands for U_{OCV} and $f(x)$ for *SOC*.

The data were fitted by the data fitter to obtain the U_{ocv}–*SOC* fitting curve, as shown in Figure 7, with a goodness of fit curve of up to 99.8%, and the parameter fitting results are shown in Table 3.

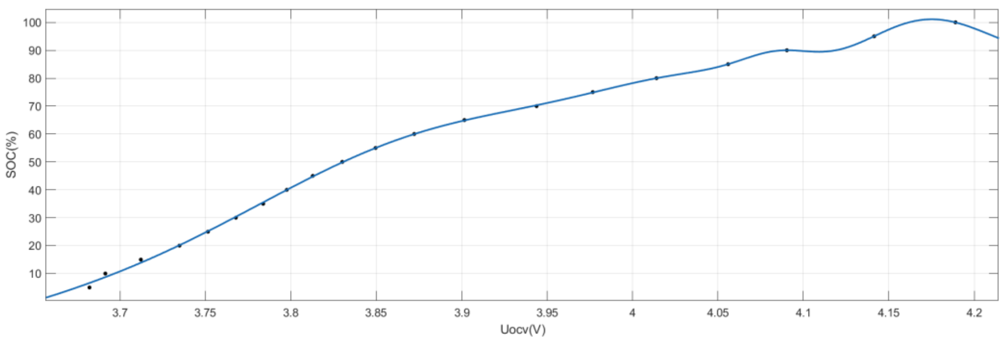

Figure 7. U_{ocv}–*SOC* fitting curve.

Table 3. Parameter fitting results.

n	a_n	b_n	c_n
1	8.719	4.555	0.7213
2	-2.342×10^{13}	7.942	7.942
3	−0.1139	4.126	0.1168
4	9.001	−9.276	10
5	0.1401	3.839	0.08771

In the constant temperature environment of 20 °C, the lithium battery with a capacity of 1000 mAh is tested for constant current discharge, and the lithium battery model is simulated and tested. The model simulation accuracy can be obtained by comparing the simulated terminal voltage and the actual terminal voltage value, and the comparison results are shown in Figure 8; the maximum relative error between the terminal voltage simulation value and the actual value is only 0.56%, and the model simulation accuracy is 99.4%.

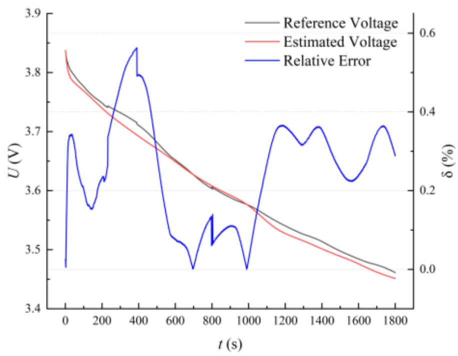

Figure 8. Comparison of battery terminal voltage simulation and experimental results.

4. *SOC* Estimation Model Establishment

Based on the above UAV lithium battery equivalent model and parameter identification results, the *SOC* estimation model of UAV lithium battery is established using MATLAB/Simulink R2022b software. The input of the model includes the real-time current and voltage of the UAV lithium battery, and the output of the model is the *SOC* of the battery, which consists of the reference SOC_1 calculation module, the parameter lookup table module, and the *SOC* calculation module. Among them, the reference SOC_1 calculation module mainly utilizes the ampere-time integration method to obtain the *SOC* reference value of the parameter lookup table module; the input of the module is the real-time current of the lithium battery, the output of the module is the SOC_1, and the module is shown in Figure 9.

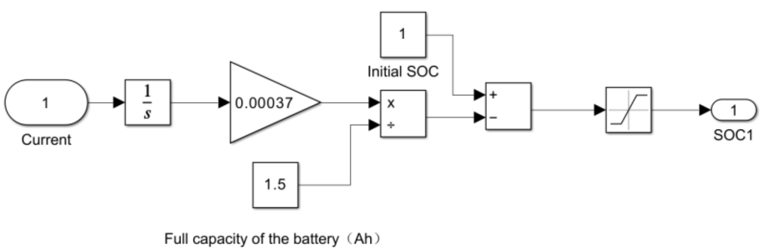

Figure 9. The reference SOC_1 calculation module.

As shown in Figure 10, the parameter lookup module uses the Lookup in the toolbox to find the corresponding ohmic internal resistance R_0, polarization resistance R_1, and polarization capacitance C_1 of the lithium battery in each *SOC* state according to the SOC_1 output by the reference SOC_1 calculation module.

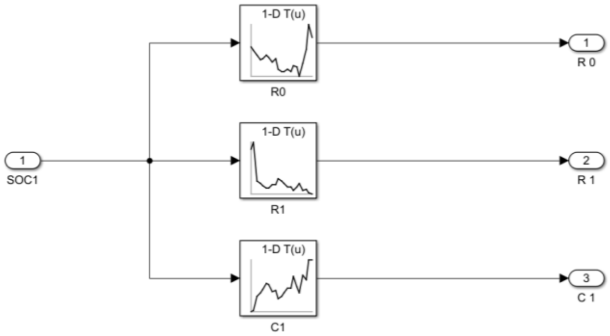

Figure 10. Parameter lookup module.

The input of the *SOC* calculation module is ohmic internal resistance R_0, polarization resistance R_1, and polarization capacitance C_1, real-time current and voltage of lithium battery, and the *SOC* of a lithium battery can be calculated according to the mathematical expression of electromotive force U_{OCV} (9) and the U_{OCV}–*SOC* fitting Equation (10), as shown in Figure 11.

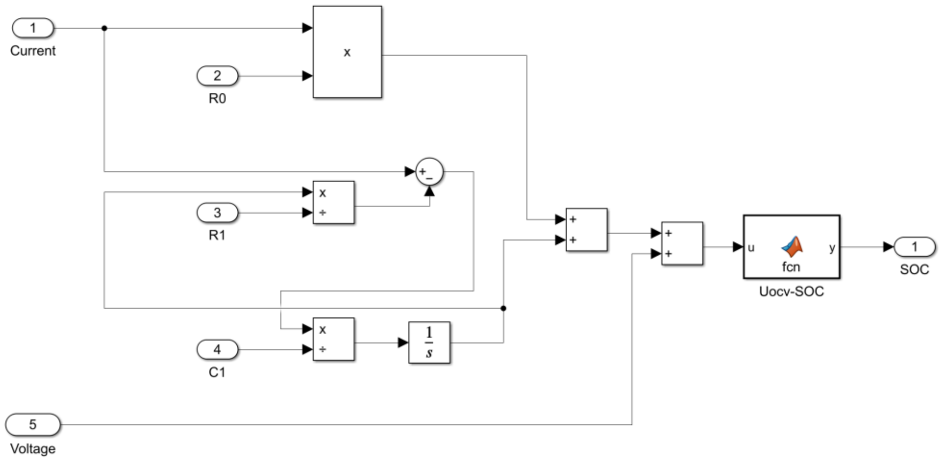

Figure 11. *SOC* compute module.

5. Device Development and Performance Verification

Aiming at the engineering needs of the UAV lithium battery *SOC* estimation model that requires real-time input of real-time current and voltage of lithium battery, the UAV lithium battery status online monitoring module is designed. The module includes a lithium battery current and voltage measurement unit, a wireless communication unit, an adapter circuit board, a power supply, and a case. The lithium battery current and voltage measurement unit is a high-precision voltage and current measurement module model INA226, which can measure and collect the current and voltage of the lithium battery of the UAV in real time, with a measurement error of only 0.05%. The wireless communication unit is a TTL-Wi-Fi transmission module model DT-6, which can transmit the data collected by the measurement unit to the control terminal via Wi-Fi, and the ideal communication distance can reach 100 m. According to the interface settings of the measurement unit and the communication unit, an adapter board connecting the two units is designed using Altium Designer 19 software, and the circuit diagram of the adapter board is shown in Figure 12; it can realize the electrical connection between the measurement module and the communication module. The power supply of the module selects a 5 V constant voltage lithium battery, which can supply power to the module and set up a mechanical switch to control the module power on and off. According to the internal circuit board and power supply size, the use of SolidWorks 2022 software for the module of the overall space layout and shell design, the module size is 70 mm × 62 mm × 27 mm, and the module physical drawing is shown in Figure 13.

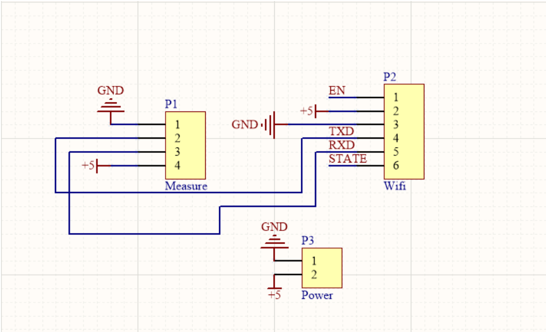

Figure 12. Interposer circuit diagram.

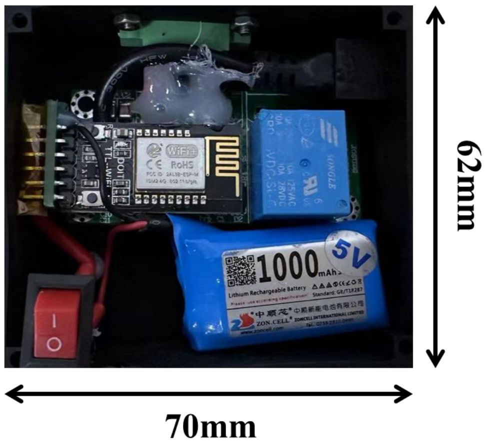

Figure 13. Physical diagram of lithium battery online monitoring module.

The lithium battery online monitoring module is connected to the positive and negative poles of the UAV and the UAV lithium battery, respectively. When the module switch is turned on, the lithium battery current and voltage can be measured in real time and the serial port assistant on the PC side sends the AT instruction to the module in real time. Then, the module receives the instruction and seamlessly transmits the current and voltage data to the PC in real time via Wi-Fi, and the data are processed in real time via the data identification program of MATLAB R2022b software. The model is imported into the model after processing, and the model is calculated and outputs the lithium battery *SOC* estimation results. The schematic diagram of the online estimation of *SOC* for UAV Li-ion battery is shown in Figure 14.

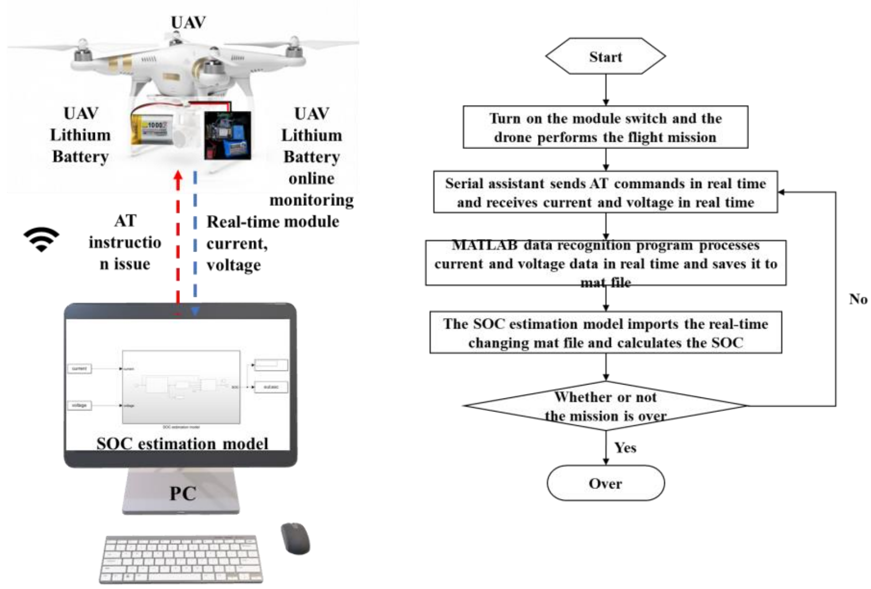

Figure 14. The schematic diagram of the online estimation of *SOC* for UAV Li-ion battery.

The serial port assistant saves the current and voltage data in DAT file format to the desktop in real time, and the MATLAB data recognition program is shown in Figure 15. The program reads and recognizes the string containing "+V=" and "+A=" in the file cyclically, extracts the corresponding current and voltage from the string, and saves them to the mat file in MATLAB work in chronological order until the program stops. The corresponding current and voltage are extracted and arranged in chronological order and saved to the mat file in MATLAB work until the program stops and the mat file keeps refreshing the data to ensure that the data can be imported to the *SOC* estimation model in real time.

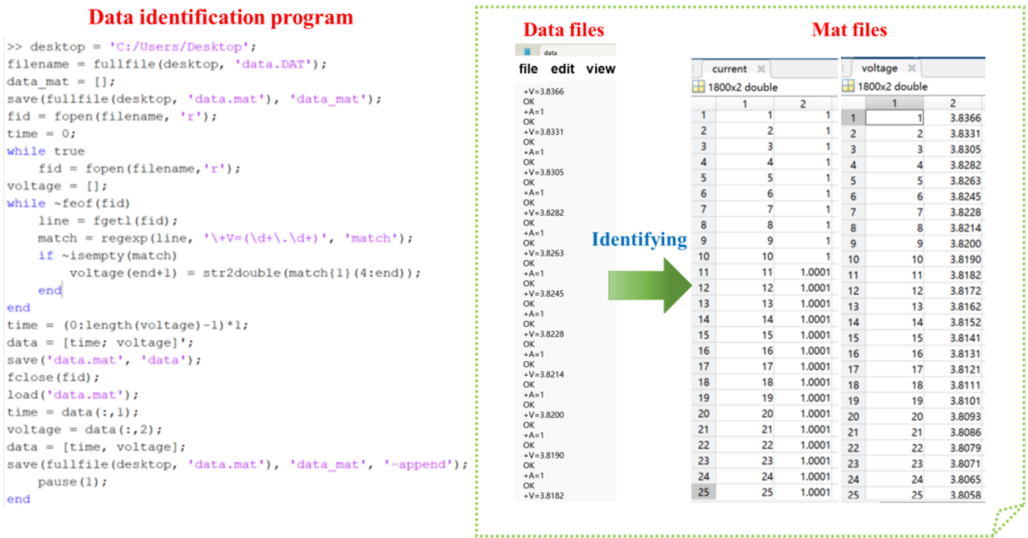

Figure 15. Data identification program.

Under the constant temperature environment of −5 °C, 20 °C, and 40 °C, the battery tester is utilized to simulate the discharge of the lithium battery under the working condition of the UAV, and the online monitoring module is connected to the positive and negative poles of the battery tester and lithium battery, respectively, and the discharge condition is set to be 1C constant current discharge for 30 minutes, so that the real-time online estimation of *SOC* is carried out for the lithium battery of the UAV, and the *SOC* estimation model in the process of experimentation can show the real-time display of *SOC* status of the lithium battery of the UAV as shown in Figure 16.

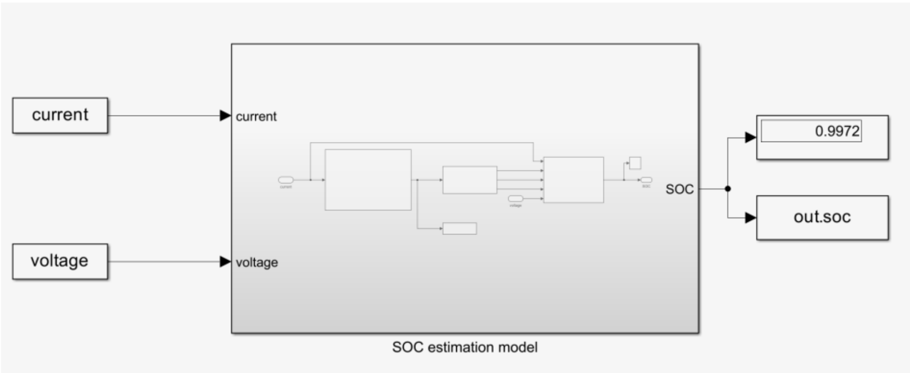

Figure 16. *SOC* estimation model real-time estimation interface.

Shown in Figure 17a–c are the comparison graphs of reference *SOC* and estimated *SOC* curves of the UAV lithium battery under three temperature conditions of −5 °C, 20 °C, and 40 °C, respectively, and the comparison curves of the *SOC* estimation errors under three temperature environments are shown in Figure 18. The results show that the maximum absolute error Δ_{max} of the scheme's *SOC* estimation is 1.679%, and the estimation accuracy is 98.3%, which meets the requirements for the estimation accuracy of the residual power of the lithium battery of a small UAV. The scheme can realize the real-time online estimation of the *SOC* of the UAV lithium battery, and the response time is less than 1 s, with good real-time performance. The method can be applied to the real-time online estimation of *SOC* of different models of UAV lithium batteries, with strong generality.

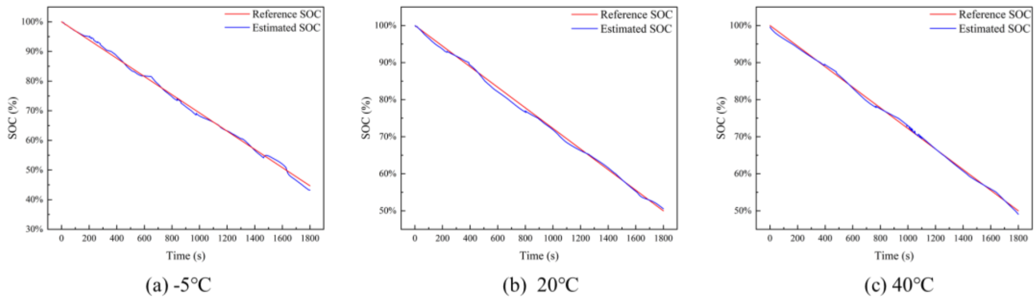

Figure 17. Reference *SOC* vs. Estimated *SOC*: (**a**) −5 °C; (**b**) 20 °C; (**c**) 40 °C.

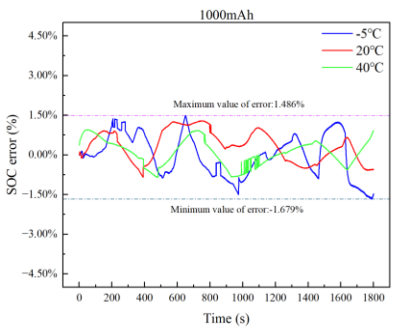

Figure 18. *SOC* estimation errors.

6. Conclusions

Aiming at the problems of low estimation accuracy and poor real-time performance of the current UAV lithium battery *SOC* estimation, the existing UAV lithium battery *SOC* estimation methods are first analyzed and compared, and then a real-time online estimation scheme of the UAV lithium battery *SOC* state is proposed. A model-based approach is adopted to analyze and discuss different battery models, and the Thevenin model is selected for the UAV. The Thevenin model was chosen to model the UAV Li-ion battery equivalently, and the model was verified by parameter identification and simulation. Based on the battery equivalent model and parameter identification results, the *SOC* estimation model of the UAV lithium battery was established, and the online monitoring module for UAV lithium battery was developed. Finally, the *SOC* real-time online estimation experimental test is carried out on the UAV lithium battery.

The simulation test results prove that the simulation accuracy of the UAV lithium battery equivalent model can reach 99.4%; the results of the *SOC* real-time online estimation experimental test show that the *SOC* real-time online estimation scheme proposed in this study can realize the *SOC* online estimation of the lithium battery of the UAV with high precision, and the estimation accuracy can reach 97.4%, which can satisfy the requirements of the UAV for the accuracy of *SOC* estimation. At the same time, this scheme has the advantages of good real-time performance and strong versatility, and the program has the advantages of good real-time and strong generalization.

However, due to the limitation of experimental conditions, this scheme has not been applied to the *SOC* estimation of lithium batteries under the working conditions of actual UAVs. Compared with the laboratory conditions, the real-time online *SOC* estimation of UAVs under actual working conditions is susceptible to the influence of noise interference, load changes, temperature changes, and other factors, thus generating errors and leading to a decline in estimation accuracy. We will also consider adopting suitable methods to compensate for and correct the errors of noise, load, temperature, and other factors so as to further improve the accuracy of the real-time online estimation of the *SOC* of lithium UAV batteries and to strengthen the applicability of the real-time online estimation program of the *SOC*.

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