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Online parameter identification for equivalent circuit model of lithium-ion battery

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ABSTRACT

Parameter identification is the most fundamental task for the model-based battery management system. However, there are some difficulties in completing this task since most of the existing methods require at least one known parameter or a time-consuming offline procedure to extract parameters from measured data. Based on the well-known thevenin equivalent circuit for battery, this paper determines the unique purpose is introducing the bounded varying forgetting factor recursive least square approach which identifies online all the parameters of the battery model at the same time. The precision of the proposed method is verified by simulation with the error converged to zero and the maximum error less than 1% of the nominal value.

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1. INTRODUCTION

The increasing concerns for environmental protection and the energy crisis have propelled the rapid growth of electric vehicles (EVs) in recent years. Among various battery technologies, lithium-ion batteries have been preferred for EVs because of their high power-to-weight ratio, long cycling lifespan, and low self-discharge. To ensure the reliable and efficient performance of EVs, accurate prediction of battery performance is crucial [1], [2].

Battery management systems (BMS) have increasingly relied on model-based estimation techniques in recent years, with battery modeling emerging as a critical factor affecting estimation accuracy. These models simulate battery reactions and inform charging and discharging strategies. Besides the electrochemical model [3]–[5], and the black box model [6], the equivalent circuit model (ECM) [7]–[10] is widely used due to its simplicity of battery simulation [11]. In the ECM, the voltage response of a battery can be well modeled on different time scales by connecting RC cells with different time constants in series [12], [13].

Much of the recent research is based on a circuit model that simulates the electrical dynamics of a battery using a network of resistors, capacitors, and voltage sources. However, the ECM parameters often change under real conditions or drift during charge/discharge cycles [14]. This raises the question of how accurately and effectively we can identify them by measuring the current/voltage across the battery cells. In the current literature review, the ECM's parameters identification method can be divided into three categories.

Offline experiment-based examination. This classification uses charging/discharging examinations with the final goal that a battery's parameters can be estimated from the dynamics. The transient voltage response is utilized in [15] to find the ECM's parameters by charging/discharging a battery utilizing constant and pulse currents. The state-of-charge (SOC)-open circuit voltage (OCV) relationship can be used for the estimation of SOC. This can be done by the small current discharge experiment [16], or on the other hand, by applying a typical magnitude discontinuous current (an adequately long rest period is applied between two discharge cycles) [17]. While simple to implement, these methodologies present huge time costs-a SOC-OCV alignment investigation can require over one day [18], excessively expensive, particularly in enormous battery testing.

Electrochemical impedance spectroscopy (EIS). EIS is a significant method for noticing electrochemical cycles inside batteries. The EIS information uncovers the battery impedance characteristic, and the writing incorporates a couple of techniques that fit an ECM to gather EIS information to separate the obstruction and RC boundaries [19]. These techniques center around impedance recognizable proof on a case-by-case basis in numerous applications and then, leave different information about a battery's elements for example the SOC-OCV relationship is ignored.

Online data-based parameter estimation. This classification tries to use the current/voltage measurements to decide an ECM's parameters from a system identification viewpoint. The effort on online model boundary recognizable proof of lithium-ion battery has hatched numerous techniques, which can be characterized into filtering-based and regression-based strategies. The first sort of technique utilized various kinds of adaptive filters [20] for online tracking of time-varying ECM's parameters. However, the generally high computational burden brought by high-order matrix manipulations is not suitable for onboard systems in real applications. On the other hand, the regression type of approaches which are mostly based on least squares (LS) is more widely used because of their lower computing effort. The researches [21], [22], the LS moving window was used to update the first-order RC model parameters and estimate the SOC with high accuracy. In contrast to the batch calculation features of LS, the recursive least squares (RLS) method [23] has been most widely used to identify LIB model parameters due to its reasonable computational requirements and recursive calculation framework. However, it is difficult to deal with the saturation issue if the parameters suddenly change or change extremely slowly, resulting in the RLS method having its limitations. In a few studies, the forgetting factor (FF) has been introduced or combined with filtering algorithms to improve the RLS method. It is common for the FF to be set to constant values, which leads to unsuitable performance under complex and unpredictable working conditions. Furthermore, since the filtering algorithms have been integrated, the matching between them and the overall computational efficiency is compromised. With the identification of parameters, the workload for the joint estimation of SOC and some of the model parameters increases [24]. It should be emphasized that these studies often require an accurate SOC-OCV connection to be established before identification, which necessitates the previously described long-term testing.

Although crucial, the methods mentioned earlier are subject to two main limitations. They only identify a subset of an ECM's parameters, assuming that the other parameters are already known. Additionally, the FF is frequently set to a constant value, which is not suitable for complex and changing operating conditions in practice. This raises an intriguing question: Can an ECM's parameters be extracted simultaneously? By "all," we refer to both the RC parameters and the nonlinear SOC-OCV function parameters. Achieving this would yield at least two benefits. Firstly, it would significantly enhance battery model identification efficiency by eliminating the time-consuming SOC-OCV calibration process. Secondly, without the need for offline measurement, it would ensure the availability of an accurate battery model for management throughout various load scenarios.

This work is propelled to develop new methodologies with VFF to distinguish successful online battery estimation for one-cycle battery parameters identification. The well-known thevenin model is considered here. Due to the nonlinearity of the model, the identification process can be spiked, which may lead to unphysical estimation. This work thus presents a precise approach to defeat this problem, with these accompanying commitments.

This work brings to reality the novel one-shot parameter identification methods which were developed to estimate all the parameters one at a time without any information except current and voltage and minimize the model prediction error by setting the boundaries of trust-region for the parameters. An online estimate approach based on variable forgetting factor recursive least squares is presented. In the optimization of the RLS method, we demonstrate that the VFF converges to the real value in real time via linear correlation with the system's iterative error and gain. Therefore, the online real-time estimation of the parameter can be achieved accurately.

This research introduces a method of estimation of all the parameters in the thevenin battery model without any information further than measured voltage and current. The accuracy of this method is better than other existing methods with a terminal voltage error of less than 1% of the nominal voltage. The estimated internal resistance is also compared with real measurements by a battery tester and guarantees the precision of the identification.

2. LITHIUM BATTERY MODELING

2.1. Equivalent circuit model

From the dynamic response of the cells, the equivalent circuit model consists of electrical components such as a resistor, capacitor, and voltage source to mimic the same dynamic response of the battery so that it can be used as the model for a battery with much lower complexity in comparison with the electro dynamic model. Figure 1 is an ECM with a voltage source U_{OC} represents the open circuit voltage, resistor R_o represents series resistance, several parallel branches $R_{D_k}C_{D_k}$is applied to represent the transient response of terminal voltage. The input of the model is the current i_L, the output of the model is the terminal voltage U_t.

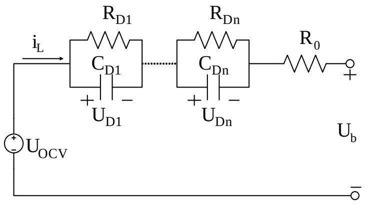

Figure 1. Equivalent circuit of a lithium battery

2.2. Battery mathematic model

Various R-C models with differing numbers of parallel branches have been developed for batteries, depending on the intended application and desired level of accuracy. The number of parallel branches of R-C is a tradeoff between accuracy and complexity. However, one R-C model is accurate enough for EV applications [21]. Thus, the thevenin model is chosen to be investigated. The one R-C thevenin equivalent circuit model is shown in Figure 2.

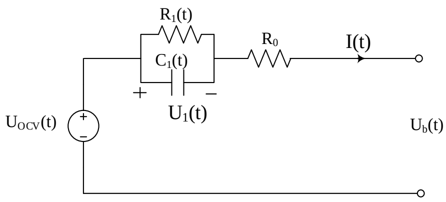

Figure 2. One R-C thevenin ECM

The thevenin model can be presented in the s-domain as:

$$\begin{cases} \dot{U}_1(s) = \frac{I(s)}{C_1} - \frac{U_1(s)}{R_1C_1} \\ U_b(s) = U_{OCV}(s) - U_1(s) - R_0I(s) \end{cases} \tag{1}$$

relation between terminal voltage and open circuit voltage:

$$U_b(s) - U_{OCV}(s) = -I(s)\left(R_0 + \frac{R_1}{1+R_1C_1s}\right) \tag{2}$$

the transfer function is obtained:

$$G(s) = \frac{E_L(s)}{I(s)} = -R_0 - \frac{R_1}{1+R_1C_1s} = -\frac{R_0+R_1+R_0R_1C_1s}{1+R_1C_1s} \tag{3}$$

where,

$$E_L = U_b - U_{OCV}$$

after the discretization of G(s) by Tustin's method, with $s = \frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}}$, the transfer function is:

$$G(z^{-1}) = -\frac{\frac{R_0T+R_1T+2R_0R_1C_1}{T+2R_1C_1}+\frac{R_0T+R_1T-2R_0R_1C_1}{T+2R_1C_1}z^{-1}}{1+\frac{T-2R_1C_1}{T+2R_1C_1}z^{-1}} \tag{4}$$

the (4) can be written as (5) after discretization with k=1, 2, 3, …,

$$E_L(k) = a_1E_L(k-1) + a_2I(k) + a_3I(k-1) \tag{5}$$

where, $a_1 = -\frac{T-2R_1C_1}{T+2R_1C_1}, a_2 = -\frac{R_0T+R_1T+2R_0R_1C_1}{T+2R_1C_1}, a_3 = -\frac{R_0T+R_1T-2R_0R_1C_1}{T+2R_1C_1}$

The synthetic influence on the OCV is determined by various factors including the SOC, working temperature (Te), and cycle history (H). These factors can all be mathematically represented as functions of time (t). Therefore, the correlation between these factors can be defined as (6).

$$\frac{dU_{OCV}}{dt} = (\frac{\partial U_{OCV}}{\partial SOC}\frac{\partial SOC}{\partial t} + \frac{\partial U_{OCV}}{\partial Tem}\frac{\partial Tem}{\partial t} + \frac{\partial U_{OCV}}{\partial H}\frac{\partial H}{\partial t}) \tag{6}$$

If the change in SOC during the sampling time is negligible, we can assume that ∂SOC/∂t≈0. Additionally, as the battery is typically heated or cooled to reach the working temperature, we can assume that the temperature change is relatively small and ∂Te/∂t≈0. In the long-term usage history, short-term cycles have minimal impact on the cycle history (H) value. Therefore, we can also assume that ∂H/∂t≈0. As a result, we can rewrite (6) as:

$$\frac{dU_{OCV}}{dt} = \frac{U_{OCV}(k)-U_{OCV}(k-1)}{T} \approx 0 \tag{7}$$

$$\triangle\, U_{OCV}(k) = U_{OCV}(k) - U_{OCV}(k-1) \approx 0 \tag{8}$$

from the (5) and (8) terminal voltage $U_b(k)$ is obtained:

$$U_b(k) = (1-a_1)U_{OCV}(k) + a_1U_b(k-1) + a_2I(k) + a_3I(k-1) \tag{9}$$

with $\phi = [1, U_b(k-1), I(k), I(k-1)]$ and $\theta = [(1-a_1)U_{OCV}(k), a_1, a_2, a_3]^T$, from (9) we obtain:

$$U_b(k) = \phi.\theta \tag{10}$$

the recursive formulas can be used to identify the parameter vector θ, from which we can derive the values of the model parameters $R_0, R_1, and\ C_1$ by utilizing the expressions of $a_1, a_2, and\ a_3$.

3. PARAMETER IDENTIFICATION

By constraining the search within a parameter space that can be believed to be correct, it is possible to prevent parameter searches from reaching physically meaningless local minima. A limited search space can be created based on the lower and upper bounds of several parameters, then numerical optimization can be performed within the boundaries of this space. There is no difficulty in determining the bounds for some parameters in thevenin's model since observation and analysis of measurement data can both provide some coarse-grained knowledge of a battery, for example, internal impedance.

The ECM-based recursive least squares (RLS) parameter identification approach, among others, is particularly suited for such complex BMS situations [25]. However, one major essential concern with RLS is that the method might become numerically unstable due to a lack of excitation of the battery model by the measured quantities measurement inputs. This article addresses these issues while reaping the benefits of RLS by adaptively changing the forgetting factor which is called varying forgetting factor recursive least squares (VFFRLS). In VFFRLS, the exact forgetting factors are tracked with simple calculations using recursive relationships between RLS variables.

Estimated terminal voltage:

$$y_k = \phi_n(k)\theta_n(k) + e(k) \tag{11}$$

the error between the measured voltage and the estimated one:

$$e(k) = U_b(k) - \phi_n(k)\hat{\theta}_n(k-1) \tag{12}$$

gain of RLS:

$$K(k) = \frac{P_n(k-1)\phi_n^T(k)}{\lambda_n(k-1)+\phi_n^T(k)P_n(k-1)\phi_n(k)} \tag{13}$$

estimated parameters vector:

$$\hat{\theta}_n(k) = \hat{\theta}_n^-(k) + K(k)e(k) \tag{14}$$

covariance of error:

$$P_n(k) = \frac{P_n(k-1)-K(k)\phi_n^T(k)P_n(k-1)}{\lambda_n(k-1)} \tag{15}$$

varying forgetting factors:

$$\lambda_n(k) = 1 - \frac{e^2(k)}{1+K^T(k)P_n(k)K(k)} \tag{16}$$

$\hat{\theta}(k)$: estimation of parameter vector θ; e(k): estimation error of the terminal voltage $U_b(k)$; K(k): gain, P(k): covariance matrix, λ: FF to perform real-time correction for changes in parameters and update the covariance matrix. The (12) and (16) embody the concept of the VFFRLS algorithm. If the error levels of the system change substantially, the algorithm quickly replaces the old data with new data to establish a new learning model that accurately reflects the current state of the system. This enables the system to rapidly adapt to changes and achieve its objective. The new learning model gradually converges as more samples are added. As the prediction error "e" ("k") decreases, the effective data window length "λ" ("k") increases, resulting in higher steady-state accuracy of the system. The Flowchart of the online parameter identification algorithm is shown in Figure 3. Initial value $\theta(0), P(0), K(0)$ is set with an appropriate value, then the estimated parameter vector θ(k) is updated with the change in measured data vector $\phi(k)$ by forgetting factor λ after each loop.

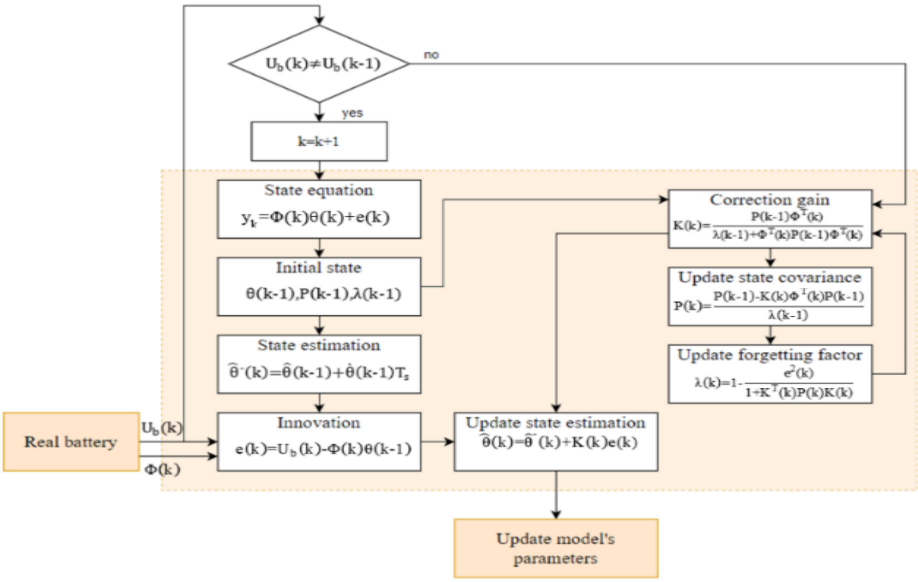

Figure 3. Flowchart of the online parameter identification algorithm VFFRLS

4. VALIDATION OF THE PROPOSED APPROACH

4.1. Method of validation

The current and terminal voltage of a lithium pin cell will be recorded in an entire charge-discharge cycle. The sampling time must be large enough to guarantee the stability of the system and small enough to track the change in the battery's dynamics. The chosen sampling time is 1 second. The precision of the VFFRLS algorithm will be examined by comparing the ECM output's terminal voltage with identified parameters and the reference measured terminal voltage. The measurement system and data logging system are set up as shown in Figure 4. An experimental model is built in Figure 5.

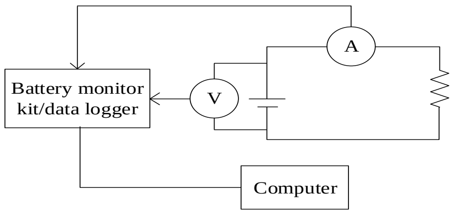

Figure 4. Block diagram of the validation experiment

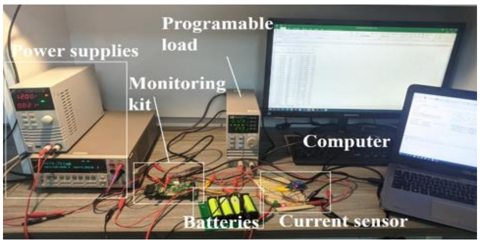

Figure 5. Experiment system model

4.2. Parameter identification result

The validation experiment is set up with a constant resistive load of 2 ohm, Figure 6 shows the battery terminal voltage and discharge current in one cycle. Discharging begins at a time of 100 seconds with a maximum OCV is 4.2 V, discharge terminated at time 5,300 seconds as the terminal voltage drops 3.1 V. The discharge current is not constant and has the same trend as the terminal voltage since the discharge load is resistive. Each curve has 5,300 measurement samples, and they will be used to estimate the model's parameters.

Figure 7 shows the estimated OCV and the model's terminal voltage. During discharge, the OCV curve is always higher than the terminal voltage since the battery is about to recover if the load is disconnected. When discharge ends, i.e., the SOC approach zero, the OCV and terminal voltage converge because the battery runs out of chemical energy, and then it is not able to recover until recharged. The estimated output of OCV is similar to the real OCV curve in the battery's datasheet.

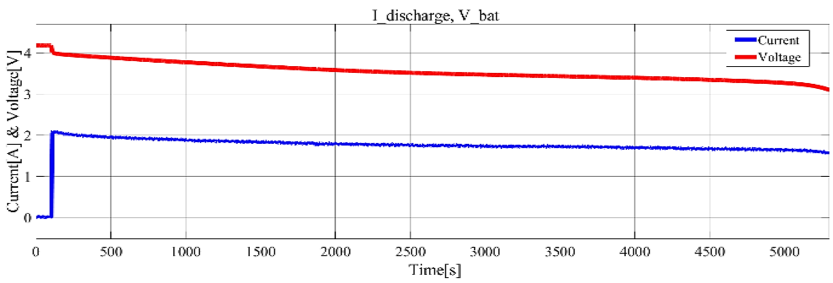

Figure 6. Measured terminal voltage and discharge current

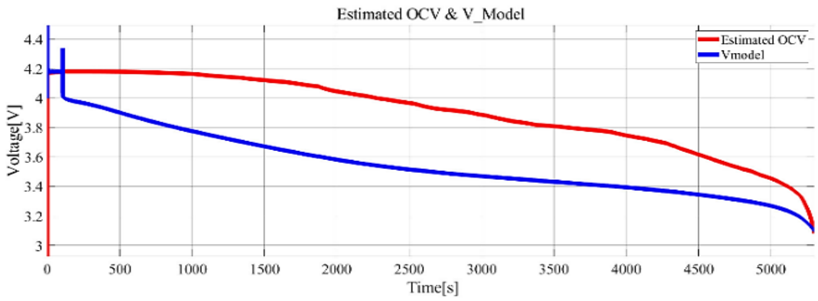

Figure 7. Estimated OCV and model's terminal voltage

The results of the estimation of parameters are shown in Figure 8. Figures 8(a)-8(c) are the estimated results of parameters R_0, R_1, and C_1 respectively. R_0 reflects the ohmic resistance of the battery. With time smaller than 100 seconds, the current is equal to zero due to load disconnection then the resistance can not be estimated effectively. From time large more than 100 seconds when the load is connected, resistance R_0 fluctuates slowly around 50 mΩ. The estimated R_0 the curve is smooth with very small fluctuation after 1,000 seconds and approaches 20 mΩ at the end of the discharge cycle. This result is close enough to measure resistance by the battery tester. As the battery discharges, the R_1 and C_1 curves grow, indicating that the time constant of the RC branch is also rising, this indicates that the voltage drop on the RC branch is reducing, and the OCV and measured terminal voltage converge when the discharge cycle ends.

To verify the effectiveness of the proposed method, a mathematical model of the battery on Matlab/Simulink is built and compares the model's output terminal voltage and measured terminal voltage. The results of the model voltage and measured voltage are shown in Figure 9. Figure 10 shows the error of terminal voltage. Comparing our result of estimated terminal voltage with other works, we can see that with the same thevenin battery model, our result has a maximum error of 0.025 V over a nominal voltage of 3.7 V in comparison with [9] has a maximum error of 0.040 V.

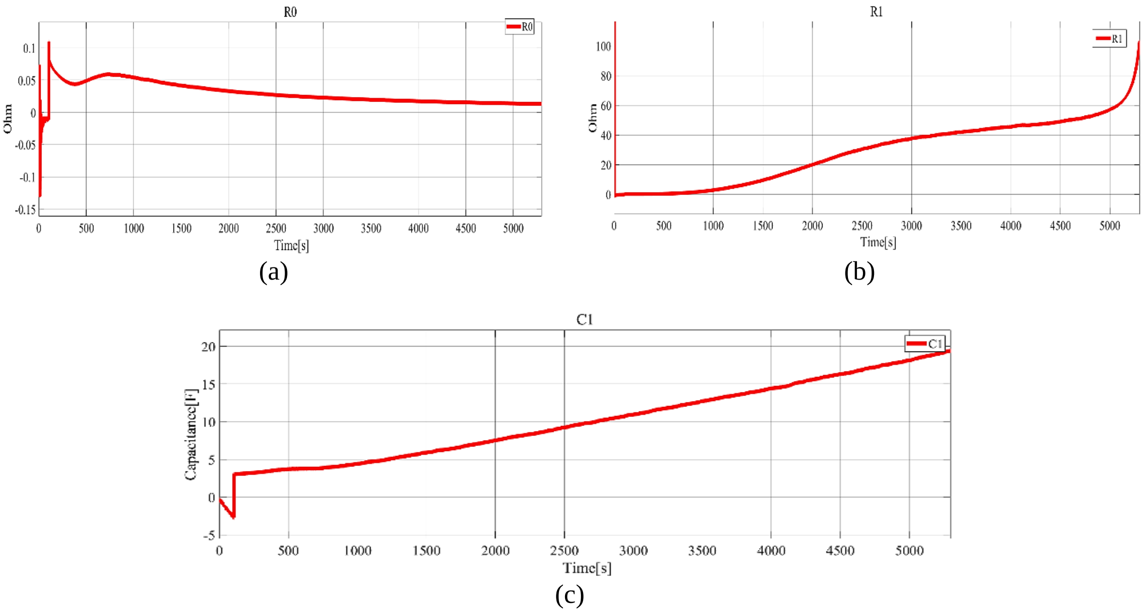

Figure 8. Estimation results of parameters (a) R_0, (b) R_1, and (c) C_1

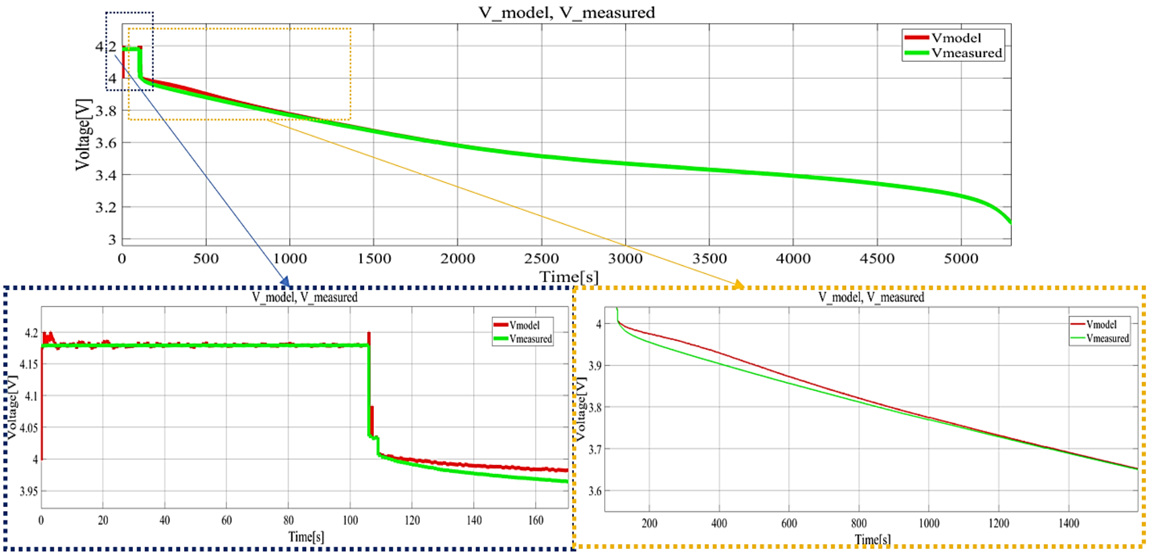

Figure 9. Model voltage and measured voltage

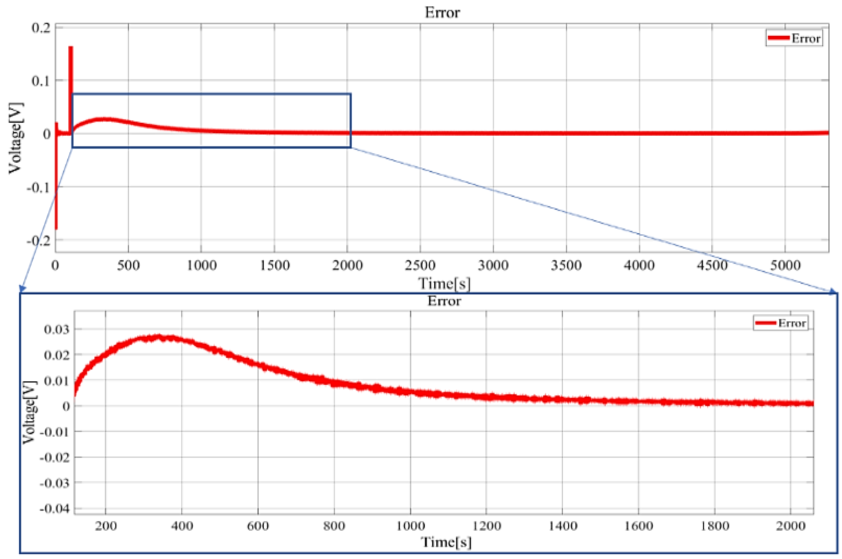

Figure 10. The error of terminal voltage

5. CONCLUSION

This paper introduces a novel approach for one-cycle parameter identification of thevenin's battery model. The main objective of this research was to develop a solution that can estimate all model parameters in real-time, based on the current/voltage data collected while the battery is running. The identified parameters were then validated by comparing the model output with measured data, with an error margin of less than 1% of the nominal voltage. The results demonstrate that the proposed method can accurately identify battery modeling, making it well-suited for a broad range of battery management applications that require precise models, including optimal charging, SOC estimation, and aging assessment. Our future work will be directed towards improving the parameter identification capability of a battery pack with dynamic stress discharge, further enhancing the practicality and versatility of this method.

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