

Online parameter estimation of a lithium-ion battery based on sunflower optimization algorithm

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ABSTRACT

For techniques used to estimate battery state of charge (SOC) based on equivalent electric circuit models (ECMs), the battery equivalent model parameters are affected by factors such as SOC, temperature, battery aging, leading to SOC estimation error. Therefore, it is necessary to accurately identify these parameters. Updating battery model parameters constantly also known as online parameter identification can effectively solve this issue. In this paper, we propose a novel strategy based on the sunflower optimization algorithm (SFO) to identify battery model parameters and predict the output voltage in real-time. The identification accuracy has been confirmed using empirical data obtained from CALCE battery group (the center for advanced life cycle engineering) performed on the Samsung (INR 18650 20R) battery cell under one electric vehicle (EV) cycle protocol named dynamic stress test. Comparative analysis of SFO and AFFRLS (adaptive forgetting factor of recursive least squares) is carried out to prove the efficiency of the proposed algorithm. Results show that the calibrated model using SFO has superiority compared with AFFRLS algorithm to simulate the dynamic voltage behavior of a lithium-ion battery in EV application.

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1. INTRODUCTION

With more electric vehicles on the road, lithium-ion battery is becoming a primary storage energy source as it provides superior performance in terms of life cycle, energy efficiency, and thermal stability compared with other technologies. In addition, lithium-ion batteries contain low toxic metal levels typically encountered in many other batteries, such as lead acid, and nickel cadmium NiCd batteries while at the same time being lightweight and compact [1]. To ensure good operation of the lithium battery, a reliable battery management system (BMS) is a must, which enables not only the supervision of the battery via different indicators (state of charge (SOC), state of health (SOH)...), but also ensures the safety and balance between cells. Among the most critical functions in a BMS is SOC estimation. The SOC estimation for all cells is an important input for balancing, energy, power calculations, SOH estimation, and so one [2], [3].

SOC cannot be directly measured. Therefore, an accurate prediction is expected from the BMS. SOC estimation algorithms can be categorized in two classes: model based, and non model-based approaches. Algorithms based on models have superior accuracy, the most used are thevenin model, the general nonlinear model, the Rint model, and so forth [4].

Sliding mode observer [5], [6], Kalman filter [7]-[9], H-filters [10], particle filter [11], [12] and sunflower optimization algorithm [13] techniques have been applied to estimate battery state of charge. The performance of these methods depends massively on the battery model precision. The battery model employed in these techniques is based on a fixed model parameters. However, when the battery is used, some parameters in the battery equivalent model are disturbed by factors such as SOC, temperature, and battery aging, resulting in SOC estimation errors. Refreshing the parameters of the model constantly also recognized as online parameter identification could effectively resolve this issue.

In this context, several methods for online parameter identification have been proposed, we list the most recent ones: H. Chaoui and H. Gualous [14], a combined strategy between adaptive control theory and state-space observer is used to achieve high estimation accuracy in the presence of parametric uncertainties. The proposed strategy allows to track in real-time the parameters deviation of the battery. Moreover, Lyapunov's direct method ensures the convergence and stability of the closed-loop estimation. X. Sun *et al.*, [15], the adaptive forgetting factor recursive least squares (AFFRLS) algorithm is applied to estimate the parameter of a second-order RC equivalent circuit model. The estimated terminal voltage is compared with the actual measured voltage to verify the correctness of the technique with battery tested under dynamic stress test DST. Z. Lao *et al.*, [16], an enhanced recursive least squares RLS named VFF-RLS (variable forgetting factor-recursive least squares) is introduced to automatically adjust the forgetting factor. The VFFRLS is used to constantly adjust the parameter of a Thevenin model. Combined with unscented Kalman filter (UKF), a joint algorithm is suggested to estimate the state of charge SOC. Y. Li, C. Wang, and J. Gong [17] a hybrid method which include fuzzy adaptive forgetting factor and recursive least squares method is established to adapt in real-time the equivalent circuit parameter. State of charge estimation was achieved through a combination of unscented Kalman filter and adaptive unscented Kalman filter in an effort to overcome the shortcomings of Kalman filters. B. Xia *et al.*, [18], the forgetting factor recursive least squares is used to constantly update the parameters of a Thevenin model. State of charge is estimated by a nonlinear Kalman filter.

The mentioned algorithms are accurate, but a part from recursive least squares (RLS) algorithm, they are computationally expensive, thus not suitable for electric vehicle application. In this paper, we propose an online parameter identification algorithm based on the sunflower optimization algorithm (SFO) that can be implemented on a chip, which suits electric vehicle application. Furthermore, this algorithm can be joint with other algorithms such as Kalman filter to estimate the state of charge or state of health of a lithium-ion battery.

To verify the real-time performance and precision of the proposed technique, a dynamic profile called dynamic stress test (DST) was conducted on the Samsung INR 18650 20R battery cell, the data employed are collected from CALCE battery group. Comparison of SFO versus AFFRLS is conducted to establish the accuracy and capability of the suggested algorithm. Results from the DST demonstrate the superiority of the model calibrated using SFO over the AFFRLS algorithm to mimic the dynamic voltage behavior of a lithium battery. This article is divided into four further sections: section 2 describes the model structure used, and reports the suggested algorithm SFO. Section 3 describe results and discussion, section 4 describes the implementation setup, results and discussion. In the end, we draw the conclusion in section 5.

2. RESEARCH METHOD

2.1. Battery modelling

To describe battery behavior, equivalent electric circuit models (ECMs) can be constructed with n times RC elements denoted by n RC model [19]. Three RC networks can simulate the dynamics of the battery with good accuracy [20]. In this work, one RC network is employed (R_1 , C_1) as illustrated in Figure 1. The RC circuit outlines the transient regime, in addition, the model contains one resistance R_0 to simulate the instant voltage drop. The open circuit voltage (OCV) is expressed in (1) with K_1 and K_0 as parameters to be identified:

$$V_{ocv} = f(SOC) = K_0 + K_1 * SOC \quad (1)$$

According to Kirchhoff's law, the terminal voltage V can be described as:

$$V = V_{ocv} - R_0 * I - U_1 \quad (2)$$

In (3) is extracted from the relation between the voltage U_1 and current i in the RC network:

$$C_1 \frac{dU_1}{dt} + \frac{U_1}{R_1} = i \quad (3)$$

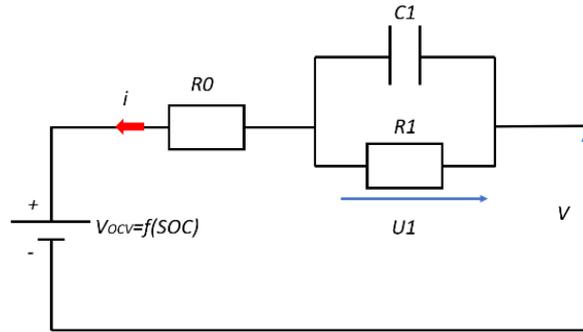


Figure 1. Equivalent circuit model

The state of charge SOC is defined as the ratio of residual capacity to total capacity. The coulomb counting is the easiest way to estimate the SOC:

$$SOC(t) = SOC(t_0) - \frac{1}{Q} \int_{t_0}^t \eta \cdot i(t) \cdot dt \tag{4}$$

Q is the rated capacity of the battery, SOC (t0) is the SOC level at the initial time t0, η is the coulombic efficiency, i(t) is the current assumed to be positive at discharge and negative at charge.

The problem of identifying the parameters is formulated in the form of a state space model. Based on (1), (3) and (5) and Figure 1, represented as follows:

$$x(k) = Ax(k - 1) + B \tag{5}$$

$$V(k) = y = Cx(k) + Du + K0 \tag{6}$$

where:

$$x(k) = \begin{bmatrix} SOC(k) \\ U1(k) \end{bmatrix}, A = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \frac{\Delta t}{R1 \cdot C1} \end{bmatrix}, B = \begin{bmatrix} -\frac{\Delta t}{Q} \\ \frac{1}{C1} \end{bmatrix}, C = [k1 \quad 1], D = -R0, u = i(k)$$

Δt represents the sampling time interval.

2.2. Problem formulation and sunflower algorithm

SFO is employed to extract the parameters (R0, R1, K0, K1, C1) of the state space model described in the previous section and to estimate the terminal voltage V(k). Because SFO is an optimizing strategy, an objective function is needed to match the estimated output voltage to the empirical voltage. The objective function utilized is based on the reduction of the square error between the empirical (real voltage) and the estimated output voltage by the algorithm.

$$F = \left(\frac{V_{hat} - V_{ex}}{V_{ex}} \right)^2 \tag{7}$$

What represents the estimated terminal voltage and Vex is the real voltage. The objective function outlined in (7) is solved by SFO subject to the below constraints with min and max as the lower and upper band values of the following parameters:

$$\begin{cases} R0min < R0 < R0max \\ R1min < R1 < R1max \\ C1min < C1 < C1max \\ K0min < K0 < K0max \\ K1min < K1 < K1max \end{cases} \tag{8}$$

2.3. Sunflower optimization algorithm

The sunflower optimization algorithm is considered as a new optimization algorithm [21-24], it is a population-based algorithm suggested in [24]. SFO mimics the sunflowers motion toward the sunlight by considering the pollination between adjacent sunflowers, if the distance between sunflowers and sun increases, the radiation intensity will decrease and vice versa according to following:

$$Srad = \frac{Spower}{4\pi d^2} \quad (9)$$

Spower is the power of the sun, and Srad depicts the intensity of the sun radiation which relies on the solar intensity and the distance squared (d) between the the sun and sunflower. The direction of every sunflower to the sun is formulated as:

$$Si = \frac{X^* - Xi}{\|X^* - Xi\|} \quad i=1,2,3,4 \dots\dots n \quad (10)$$

Xi and X^* are the present and best sunflower position, n denotes the population size, every single sunflower is pushed by (di) step towards the sun as follows:

$$di = \lambda * Pi(\|Xi + Xi-1\|) * \|Xi + Xi-1\| \quad (11)$$

λ is the sunflowers' inertial displacement, $Pi(\|Xi + Xi-1\|)$ corresponds to the pollination probability of two close sunflowers. Each sunflower's step is limited as follows:

$$dmax = \frac{\|Xmax - Xmin\|}{2 * Npop} \quad (12)$$

The positions of the sunflower are maintained inside the limits $Xmin$ and $Xmax$, where $Xmin$ and $Xmax$ being the lowest and highest constraints respectively. The $Npop$ relates to the population size. The following steps the next population towards the sun:

$$\overline{X_{i+1}} = \overline{X_i} + di * \overline{si} \quad (13)$$

The following are the SFO processing flowcharts:

- a. Initialise randomly the sunflower positions. Every sunflower presents the expected parameters within their limits $Xmax$ and $Xmin$.
- b. Compute the cost function of each sunflower and select the best position (7).
- c. Move the sunflowers towards the sun (10).
- d. while ($k < Max_iteration$)
 - for every sunflower, calculate the direction vector (10).
 - Decrease the population number by m (%): the plants further away from the sun.
 - Calculate the sunflower's step for every plant (11).
 - Fertilize the best sunflowers.
 - Assess the position for all candidates (7).
 - Identify the top candidate and upgrade the newly top position.
- e. Identify the highest position.

We used the aforementioned SFO algorithm to identify the parameters of the battery model ($R0, R1, K0, K1, C1$). The flowchart of the proposed algorithm is shown in Figure 2. The algorithm first builds the state space model and initializes the parameters of SFO. To achieve rapid convergence, we used a small $Npop$ ($Npop=5$), and fixed the max repetition rate to 10. For each new sampled value of the instant i (k) current, the algorithm computes the predicted terminal voltage using (5) and (6) and derives the objective function (7), then SFO steps in to evaluate the parameters in order to reduce the cost function. The algorithm will not stop until the cost function value is under a defined threshold, however, we allow the algorithm to bypass the SFO when the relative terminal voltage is below 1 % in order to accelerate the estimation process.

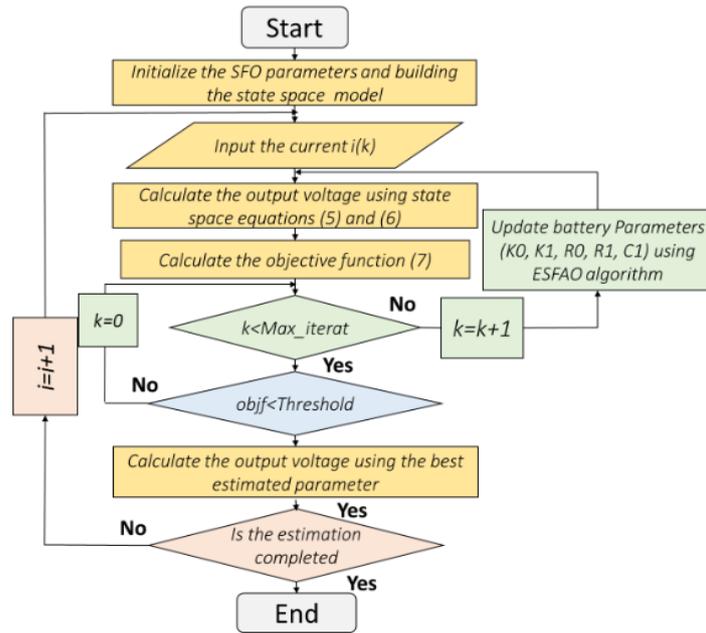


Figure 2. Flow chart of the proposed algorithm based on SFO

3. RESULTS AND DISCUSSION

We compare in this section the proposed algorithm (SFO) Figure 2 to the AFFRLS method proposed in [15]. We stress here that we will compare the algorithms (SFO versus AFFRLS) not the models. The AFFRLS parameters are obtained from [15]. Table 1 lists the proposed SFO parameters. Table 2 provides the limits of the battery's estimated parameters.

Table 1. Sunflower optimization algorithm parameter

Number of sunflowers	Pollination rate	Mortality rate	Survival rate	Maximum iteration	Threshold
5	0.1	0.005	0.9	5	10 ⁻⁴

Table 2. Identified battery parameter

	R0 (Ω)	R1 (Ω)	C1 (F)	K0	K1
Lower bound LB	0.01	100	40	0	2
Upper Bound UB	0.060	1500	120	2.5	7

To evaluate the performance of the algorithms above, we have used test data gathered from the advanced life cycle engineering center (CALCE) battery group conducted on the Samsung (INR 18650-20R) shown in Table 3. We utilized a dataset cycled under the DST protocol at 25°C [25-27].

Table 3. Characteristics of Samsung INR 18650-20R lithium-ion battery cell

Battery (Parameters)	Specifications (Value)
Cell Chemistry	LNMC/Graphite
Nominal voltage (v)	3.6
Capacity rating (mAh)	2000
Max current (A)	22

The bench battery test system used by CALCE to obtain this data includes an Arbin BT2000 battery test system to monitor battery charging and discharging, a temperature chamber to monitor temperature (not shown in Figure 3), a host computer with Arbin software to view and monitor lithium battery cell and data information [25-27]. Constant current constant voltage (CCCV) was used to charge the Samsung battery cell (INR 18650-20R). The measurements were recorded within a one-second interval. Data have been recorded for different temperatures [25-27]. We used data from a battery level of 80% at 25°C.

The DST is a common driving cycle which is often used to assess estimation algorithms and battery models, we used it here to compare the two algorithms. The current profile of this test is shown in Figure 4. We could see that this experiment has a strict charge and discharge process, the cell is highly stressed with a current that varies between +4A and -2A. Underneath these terms, the validity of the parameter identification can be well verified.

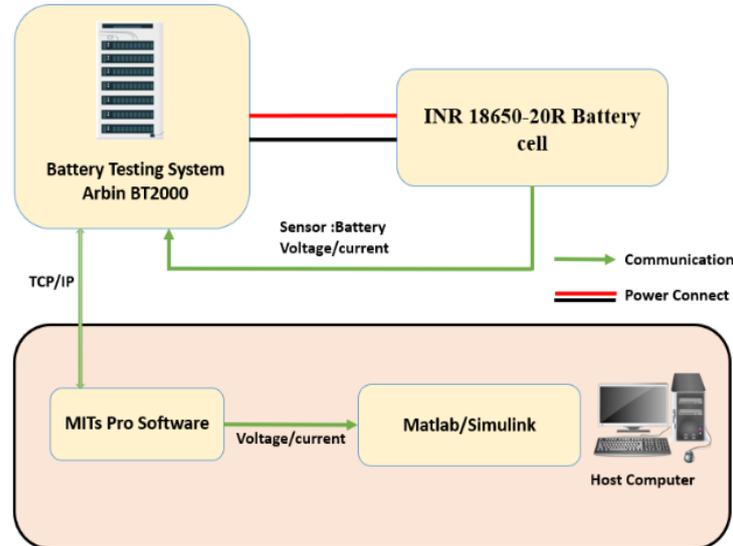


Figure 3. Schematic of the battery test bench

We run the AFFRLS [15] and SFO Figure 2 algorithms to predict the battery parameters and the terminal battery voltage. In each iteration, we supply the algorithms with the voltage and current recorded in the dataset. In Figure 5 we collected the parameter identification results for AFFRLS and SFO for the DST test. In Figure 6 we plot the output voltage estimated by both algorithms and compare it with the measured voltage (found in the dataset).

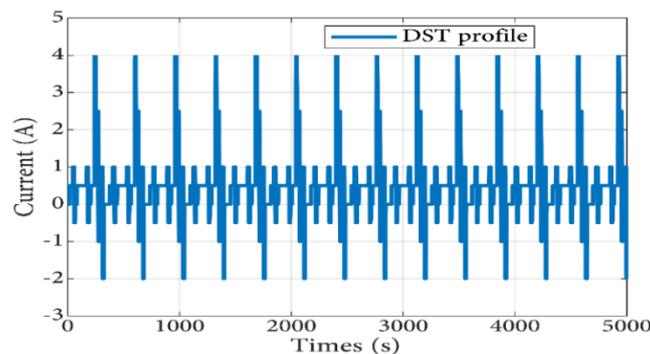


Figure 4. Current for DST profile at 25°C

It can be seen from Figure 5 that the parameters identified using SFO oscillate vigorously, the estimated parameters have more fluctuations and peaks, which is understandable since the SFO identification process relies on the use of random parameter initialization of the estimated parameters (within the defined limits in Table 2) that occur at each iteration (cycle). On the other hand, the identified parameters using AFFRLS are steadier with the exception of a rare spike in R1. AFFRLS parameters evolve smoothly with the change in current charge and discharge. The reason for this is that AFFRLS, which is an improved version of the recursive least squares RLS, takes previous results as a basis for predicting the future ones, which explains the regularity of the parameters predicted by AFFRLS compared to the SFO. For a better evaluation, we will closely examine the predicted terminal voltage. The actual terminal voltage and the predicted output

voltage determined by SFO and AFFRLS are shown in Figure 6. The terminal voltage error for both algorithms is shown in Figure 7.

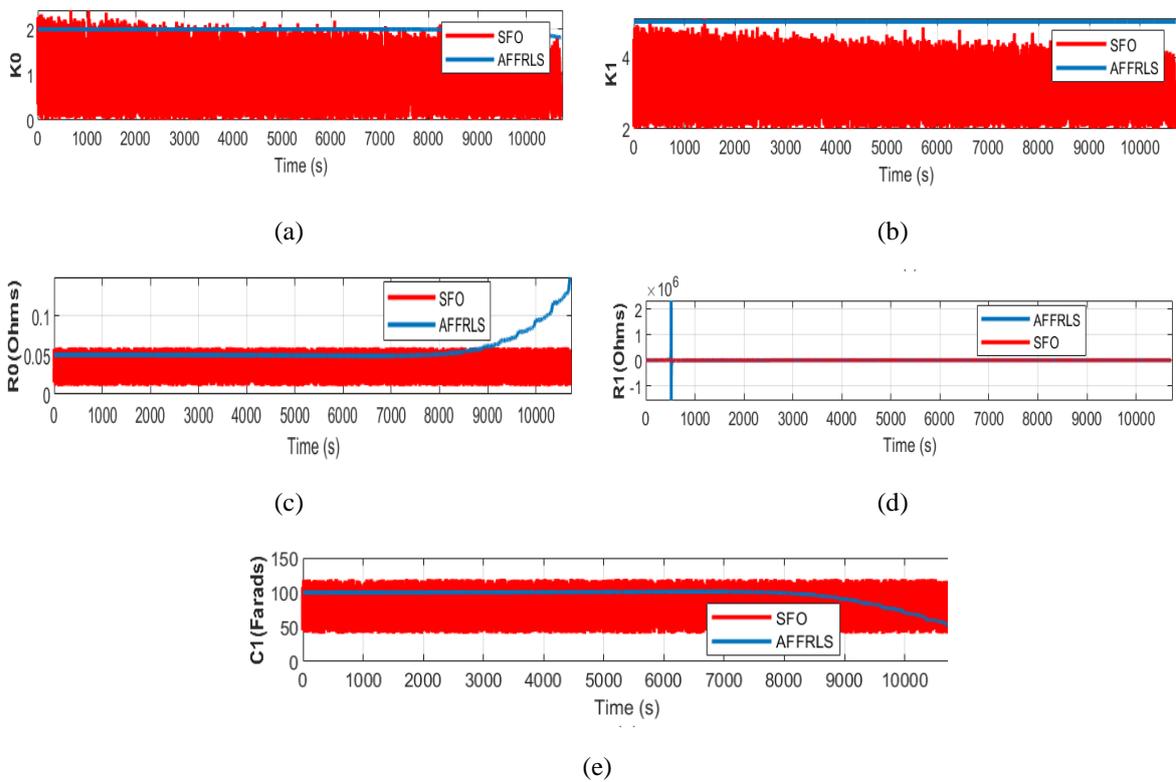


Figure 5. Parameter identification results, (a) K0, (b) K1, (c) R0, (d) R1, (e) C1

These two algorithms were capable of estimating the voltage output as depicted in Figure 6, although the SFO showed a small error voltage when compared to AFFRLS as shown in Figure 7. This implies that SFO can accurately reflect the complex characteristics of real-time variation as the battery is rapidly charged and discharged compared to AFFRLS. Table 4 summarizes the terminal voltage errors. SFO obviously has low Max, Mean and RMS (Root Mean Square) errors compared to AFFRLS as shown in Figure 6. In Figure 8, we represent the relative absolute error of the algorithms. The relative absolute error of SFO fluctuates from 0 to 1%, this is because we have specified a strict threshold for the cost function (10^{-4}). However, AFFRLS showed a relative absolute error that most of the time exceeds 2%, the recorded max value was 2.7%.

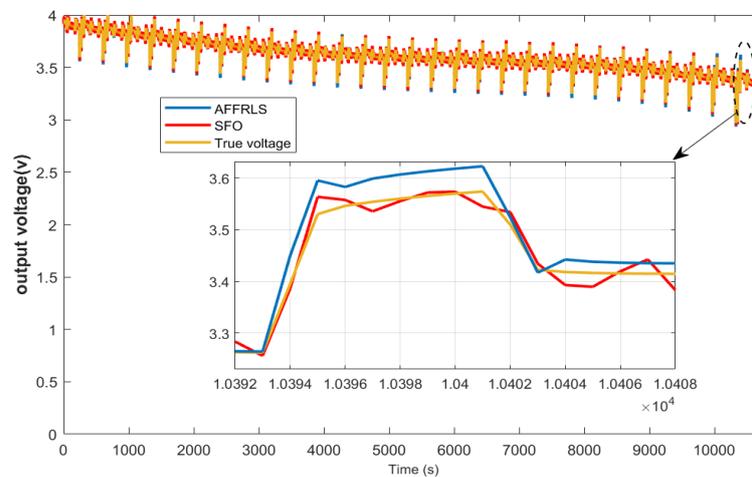


Figure 6. True and estimated output voltage by AFFRLS and SFO algorithms

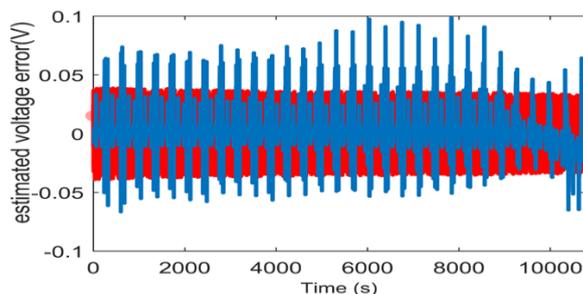


Figure 7. Estimated voltage error of AFFRLS and SFO algorithms

Table 4. Results of terminal voltage estimation

Method	Mean error (v)	Max error (v)	RMS error (v)
SFO	-0.00010	0.03926	0.0135
AFFRLS	0.0042	0.986	0.0209

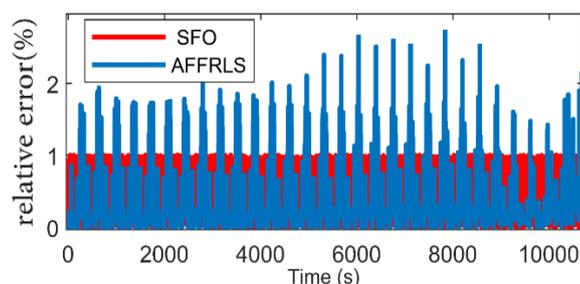


Figure 8. Absolute relative error

4. CONCLUSION

In this paper, a state-space model of a lithium-ion battery suitable for EV applications is constructed based on one RC Thevenin model. The parameters identification for the RC thevenin model using the SFO is studied and tested against the AFFRLS methodology. The predicted terminal voltage obtained using the algorithms above is compared to the actual output voltage. To compare the accuracy of the parameter identification of the equivalent circuit model, data conducted by the battery research group (CALCE) on the Samsung INR 18650-20R battery cell for an EV dynamic profile called dynamic stress test were used.

We run the algorithms using the data and compared the predicted terminal voltage. The results demonstrate that SFO outperforms the AFFRLS algorithm in modeling the battery dynamic voltage behavior. In fact, SFO managed to predict the output voltage with a relative absolute error of no more than 1% compared to AFFRLS which recorded a peak of 2.7%. This indicates that SFO is more precise than AFFRLS in its ability to identify battery parameters. As a perspective of this work, the proposed algorithm can furthermore adapted and associated with techniques such as Kalman Filtering or Particle Filtering to estimate battery state of charge or health.

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