

Parameter Identification of Equivalent Circuit Models for Li-ion Batteries Based on Tree Seeds Algorithm

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Abstract. Parameter identification method of equivalent circuit models for Li-ion batteries using the advanced tree seeds algorithm is proposed. On one hand, since the electrochemical models are not suitable for the design of battery management system, the equivalent circuit models are commonly adopted for on-board applications. On the other hand, by building up the objective function for optimization, the tree seeds algorithm can be used to identify the parameters of equivalent circuit models. Experimental verifications under different profiles demonstrate the suggested method can achieve a better result with lower complexity, more accuracy and robustness, which make it a reasonable alternative for other identification algorithms.

1. Introduction

Usage of rechargeable Li-ion batteries has aroused considerable attentions in a variety of industrial areas. Hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) are the significant areas of applications of battery technology. Accurate monitoring of battery statuses and efficient management of battery power are presently the technique bottlenecks of these electrified vehicles. Generally speaking, to enable safe, reliable and efficient operations of the power batteries under the most demanding and grueling driving conditions, an effective battery management system (BMS) must be used [1]. This system is used to inspect the conditions and states of the power battery, such as state of charge (SOC) and state of health (SOH). However, since these states are usually immeasurable by any sensors, many model-based estimation methods are used to solve the problem [2-6]. It is pretty necessary to guarantee the accuracy of battery models in order to acquire a satisfied estimated result. Besides, it is also important to balance the model complexity and accuracy in purpose to ensure acceptable estimation result while reducing calculation in real-time [7]. In brief, these models should be accurate enough and has reasonable computational burden.

The models can be categorized into two main types including electrochemical models and equivalent circuit battery models [8]. As with the former type, it is usually suitable for understanding the distributed electrochemistry reactions in the electrodes and electrolyte [9]. However, they typically deploy partial differential equations with a large number of unknown parameters, which remarkably increases the computation load. Efforts are made to simplify the structure of electrochemical models in some researches, but meanwhile several effects are ignored. Therefore, these electrochemical models are not desirable for real time battery management in electric vehicles.

For the equivalent circuit battery models, they are often lumped models with relatively fewer numbers of parameters, thus being widely applied in impedance analysis [10], SOC estimation [11], charging control [12] and SOH prediction [13]. For example, Plett [14] proposed some lumped models, such as



the simple, zero-hysteresis, one-state hysteresis, combined, and enhanced self-correcting (ESC) models and the battery SOC is estimated by extended Kalman filter (EKF) through the proposed models. Among the different kinds of equivalent circuit models, the resistance-capacitance (RC) network based models are widely researched, including the first-order RC [15-17], the second-order RC [18] and the third-order RC [19] etc. Seaman et al. [20] have conducted a comprehensive review for different types of equivalent circuit battery models. Considering the balance of model complexity and accuracy, the second-order model is regarded to be suitable for most of the applications.

However, the accuracy of circuit-based models is substantially sensitive to parameters, especially when dealing with some control-oriented problems which are essential in electric vehicle design, and thus making the identification of parameters very challenging. To be specific, the difficulty of parameter identification may due to: (1) The inconvenience of conducting EIS for frequency-domain identification; and (2) the high demand of accuracy and risk of trapping into local optimum of time-domain identification. For the latter, the unknown parameters in the governing dynamic equations can be identified from time-domain experimental data [21]. The estimation result can be improved by applying a proper global optimum algorithm. There have been some researches in the literature for parameter identification of batteries. For instance, Ouyang et al. [8] applied the genetic algorithm (GA) and Ramadesigan et al. [22] used Gauss-Newton method, a Jacobian-based scheme, for the process of nonlinear optimization in their parameter identification efforts, by minimizing an objective function that presents the discrepancy between the model outputs and the experimental one. However, those classical optimization methods are hard to achieve a satisfied result with relative lower time consume. Thus a more efficient algorithm should be applied.

In this paper, we focus on the parameter identification problem for the equivalent circuit models by using the tree seeds algorithm (TSA). Compared with other methods like Gauss-Newton method [22] and genetic algorithm [8], the tree seed algorithm (TSA) [23] has more advantages: (1) it does not require good initial values and gradient information and (2) it is proven to be more powerful to tackle with multiple mode functions. In order to achieve higher accuracy and lower time consume in parameter identification problem, the TSA is introduced. And then, the objective function based on the difference between the measured voltage and the estimated one is developed. Afterward, the improved algorithm is used to optimize the objective function and finally acquires the system parameters. The remainder of this paper is organized as follows. In section 2, we introduce the equivalent circuit battery models. In section 3, we elaborately illustrate the TSA. In section 4, the TSA is applied to parameter identification, and the comparison with genetic algorithm is presented. In section 5, some conclusions can be drawn.

2. Battery modeling and parameter identification

2.1. Description of equivalent circuit model

The equivalent circuit model used in this paper is shown in figure 1 [19], with a voltage source, an ohmic resistance and two pairs of RC networks in series. The battery dynamic and static performance can be simulated by the combination of these components. In this system, the voltage source is parameterized as a kind of nonlinear function of battery SOC and to express the open circuit voltage characteristic at different SOC. The two RC networks denote the time-dependent polarization and diffusion effects of the cell. The ohmic resistance is used to describe the instant voltage drop after an excitation current in the battery.

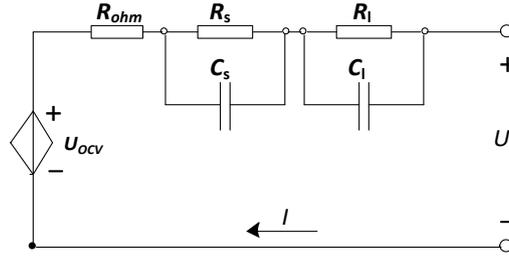


Figure 1. Battery equivalent circuit model.

2.2. Parameter identification

In the proposed method, we use the TSA to identify the ohmic resistance R_{ohm} and polarization resistances R_s , R_l and polarization capacitances C_s , C_l .

By observing figure 1, the following equations can be acquired

$$u_{ohm} = IR_{ohm} \quad (1)$$

$$C_s \frac{du_s}{dt} + \frac{u_s}{R_s} = I \quad (2)$$

$$C_l \frac{du_l}{dt} + \frac{u_l}{R_l} = I \quad (3)$$

$$u = u_{ocv} - u_{ohm} - u_s - u_l \quad (4)$$

where u is the battery terminal voltage, I is the battery current, and u_{ocv} is the open circuit voltage. R_{ohm} , R_s , R_l , C_s , C_l are the battery parameters which reflect the battery dynamic response and are needed to be identified. u_{ohm} is the voltage drop on R_{ohm} and u_s , u_l are the voltages across the two RC networks.

For further analysis, we apply discretization to the system and acquire:

$$u_k^{ohm} = I_k R_{ohm} \quad (5)$$

$$u_k^s = I_{k-1} \frac{R_s}{1+R_s C_s} + \frac{R_s C_s}{1+R_s C_s} u_{k-1}^s \quad (6)$$

$$u_k^l = I_{k-1} \frac{R_l}{1+R_l C_l} + \frac{R_l C_l}{1+R_l C_l} u_{k-1}^l \quad (7)$$

$$u_k = u_k^{ocv} - u_k^{ohm} - u_k^s - u_k^l \quad (8)$$

where k represents the time step and u^{ocv} is a nonlinear function of SOC. The function can be linearized within a short time interval:

$$u_k^{ocv} = a_k SOC_k + b_k \quad (9)$$

According to the definition of SOC:

$$SOC_k = SOC_{k-1} - I \frac{1}{C_N} \quad (10)$$

where C_N is the nominal capacity of battery and the time interval is chosen as 1s here.

$$\text{Define } x_k = [u_k^{ohm} \quad u_k^s \quad u_k^l \quad SOC_k]^T, y_k = u_k, A = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \frac{R_s C_s}{1+R_s C_s} & 0 & 0 \\ 0 & 0 & \frac{R_l C_l}{1+R_l C_l} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$B = \left[R_{ohm} \quad \frac{R_s}{1+R_s C_s} \quad \frac{R_l}{1+R_l C_l} \quad -\frac{1}{C_N} \right]^T, C = [-1 \quad -1 \quad -1 \quad a_k], D = [0 \quad 0 \quad 0 \quad b_k],$$

then these equations can be rewritten in a standard form:

$$x_k = Ax_{k-1} + BI_k \quad (11)$$

$$y_k = Cx_k + D \quad (12)$$

Based on equation (11)-(12), the output of the system can be acquired.

Here the current I is the input of system, and terminal voltage y is the output. The parameters in the system may intensively influence the input-output relation. Thus an efficient algorithm for high fidelity estimation is needed. For that, an objective function should be defined as below

$$Z = \sum_{k=1}^N e_k^2 \quad (13)$$

where e_k is the difference between the predicted output and the measured output of the model. And in this paper, the discrepancy of the voltage is used to build up the objective function, so it can be calculated as $e_k = y_k - v_k$, in which y_k is the predicted voltage at time step k and v_k is the measured voltage. Then the heuristic algorithm, such as the tree seeds algorithm can be used to minimize the error and obtain the systematic parameters.

3. Tree seeds algorithm

This heuristic algorithm is actually proposed based on the natural phenomena of trees and their seeds [23]. In reality, trees usually spread to other places through their seeds. If assuming the place for these trees and seeds as a search space for the optimization problem, the location of trees and seeds can be regarded as feasible solutions for the problem. To acquire a location of one seed that would be produced from a tree is important for the optimization problem since this procedure contains the core of search. The implement of tree seeds algorithm is shown in figure 2.

In this algorithm, the two update rules can be given as below,

$$S_{i,j} = T_{i,j} + \alpha \times (B_j - T_{r,j}) \quad (14)$$

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (T_{i,j} - T_{r,j}) \quad (15)$$

where $S_{i,j}$ is j th dimension of i th seed that would be generated i th tree. Meanwhile $T_{i,j}$ is the j th dimension of i th tree, B_j is the j th dimension of best-so-far tree location, and $T_{r,j}$ is the j th dimension of r th tree randomly picked from the colony size, α is the scaling factor arbitrarily produced in range of $[-1,1]$, besides i and r are different indices.

To balance the search capacity of the proposed search modes, it can be controlled by a parameter called as search tendency (ST) in range of $[0,1]$. The higher value of ST offers a powerful local search and speed convergence while the lower value of ST renders slow convergence but strong global search. In brief, the exploitation and exploration abilities of the TSA are controlled by this parameter.

In the beginning of operation with TSA, the tree locations (possible solutions for the optimization problem) are produced by utilizing equation (16)

$$T_{i,j} = L_{j,min} + r_{i,j} \times (H_{j,max} - L_{j,min}) \quad (16)$$

where $L_{j,min}$ is the lower bound of the search space and $H_{j,max}$ is the higher bound, $r_{i,j}$ is a random number produced for every dimension and location, in range of $[0,1]$. As with the seeds number it can be determined by the colony size (approximately between 10% and 25% of the colony size). The exact number of seed generation is utterly random in TSA.

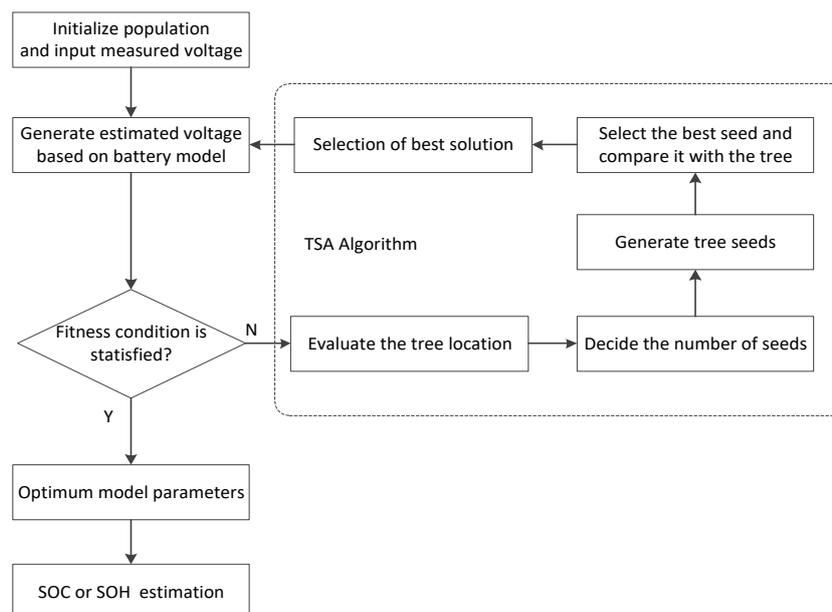


Figure 2. Flow chart of tree seeds algorithm for parameter identification.

4. Verification and comparison

In order to verify the identification result of the proposed method, a lithium nickel-manganese-cobalt oxide (LiNMC) cell with nominal capacity of 1600mAh is tested under different profiles. Here, the commonly used dynamic profiles DST and FUDS are chosen. The performance of the proposed method is evaluated by comparing the estimated voltage with the measured voltage. For further analysis, the statistic of voltage discrepancy such as MAE (the maximum absolute error) and RMSE (the root mean square error) are listed. Moreover, the identification result of genetic algorithm is attached for comparison.

The current curve of DST test is shown in figure 3. The identification results of TSA and GA under DST are shown in figure 4. For clearer comparison, the error between estimated voltage and measured voltage of the two algorithms are presented in figure 5.

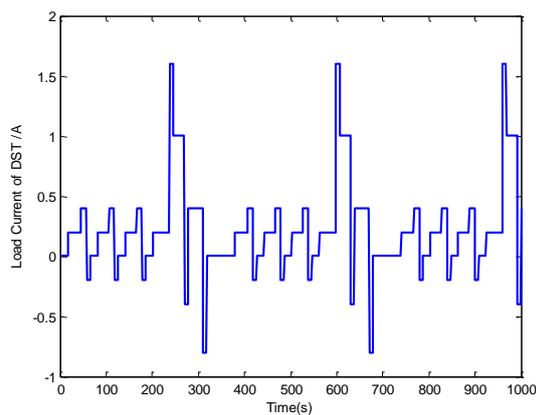


Figure 3. Current profile of DST test.

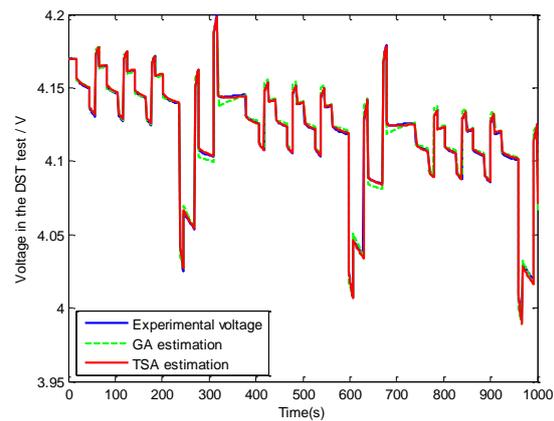


Figure 4. The measured voltage of DST test and estimation results of GA and TSA.

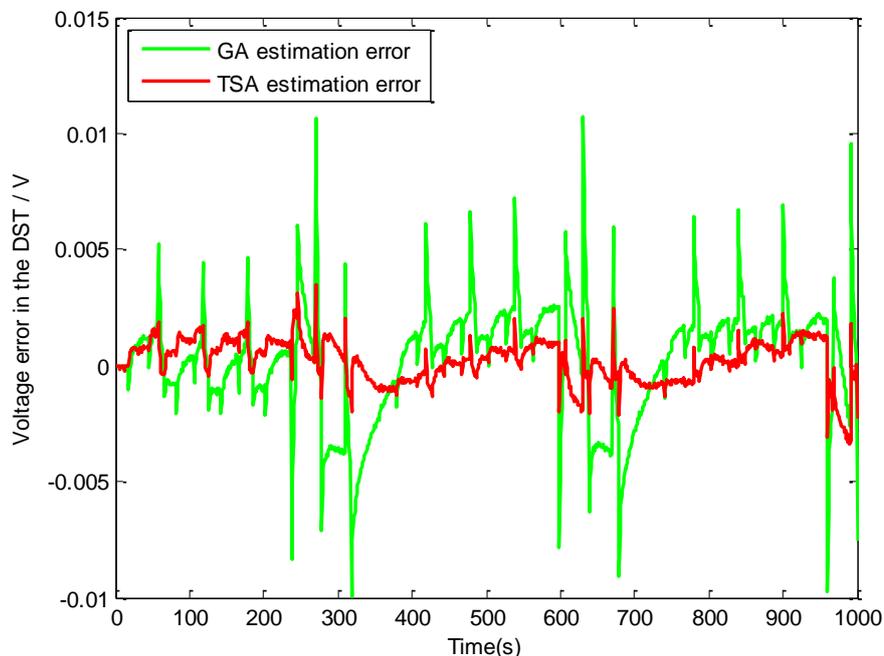


Figure 5. Voltage errors of GA and TSA in the DST test.

Similarly, the current curve of FUDS test is shown in figure 6. The identification results under FUDS are shown in figure 7 and figure 8. Table 1 lists the statistic results of identification under the two profiles.

The verification results illustrate that the proposed method has better performance in tracking the real voltage, compared with the classical genetic algorithm, thus the model accuracy can be improved.

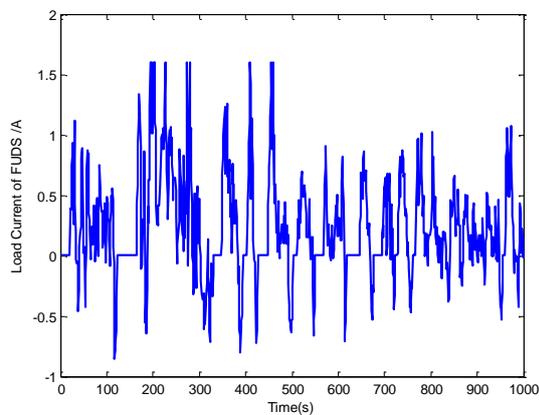


Figure 6. Current profile of FUDS test.

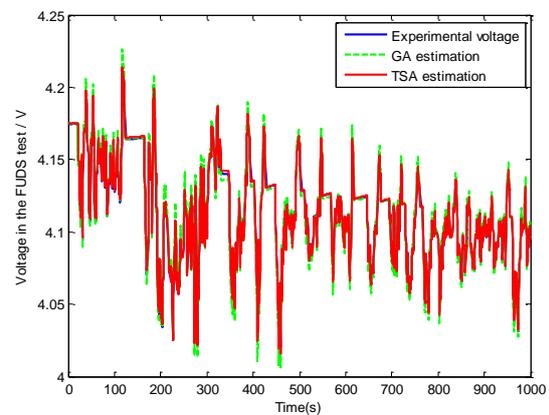


Figure 7. The measured voltage of FUDS test and estimation results of GA and TSA.

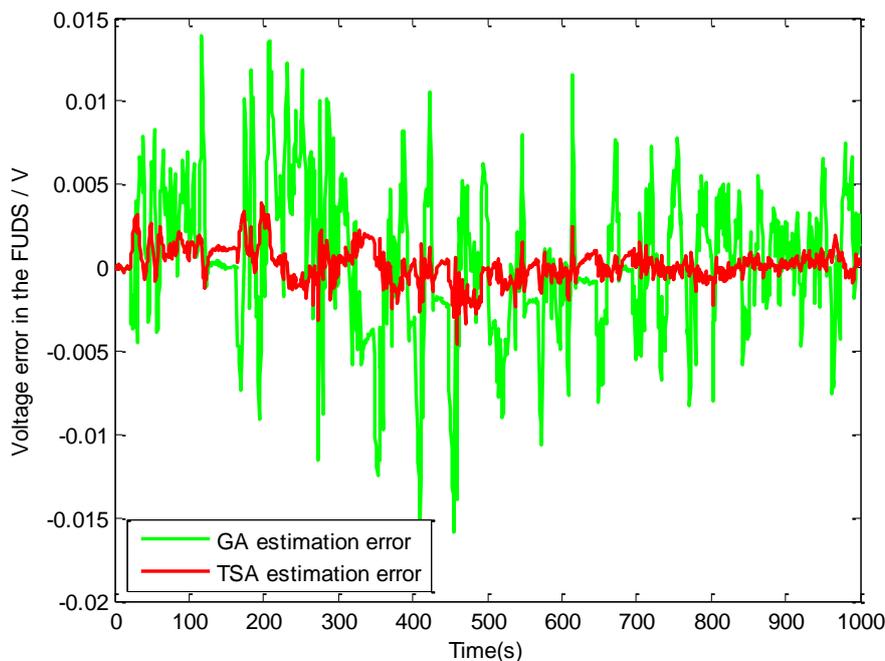


Figure 8. Voltage errors of GA and TSA in the FUDS test.

Table 1. Comparison of MAE and RMSE in the different tests.

Algorithm	DST test		FUDS test	
	MAE(mV)	RMSE(mV)	MAE(mV)	RMSE(mV)
GA	10.73	2.47	16.58	4.35
TSA	3.46	0.96	4.56	1.05

5. Conclusion

A parameter identification method based on tree seeds algorithm is presented. The sum of square of discrepancy between the measured and the estimated voltage is defined as the object function and the TSA is employed to find the optimum parameters by minimizing the function value. Experiment results show the superior performance of the proposed method over the classical genetic algorithm. The RMSE of the model is reduced by 61.1% under DST test and 75.9% under FUDS test. The

proposed method can not only improve the accuracy of the model, but also can be used for online state estimation. State variables like SOC and SOH can be estimated as one of the unknown parameters. To verify the practicability of the proposed method, the algorithm will be implemented to the real BMS in the future.

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