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Identifying the unknown parameters of ECM Model for Li-Ion Battery Using Rao-1 algorithm ‡

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Abstract: Accurately estimating the parameters for the equivalent circuit model (ECM) of lithium-ion batteries (LiBs), especially those that are not provided in the manufacturer's datasheets, is crucial for improving their behavior modeling and understanding. Therefore, this study focuses on investigating a precise method named Rao-1 algorithm, for extracting the optimal values of the ECM's parameters. The primary objective is to minimize the difference between the estimated voltage derived from the ECM and the measured voltage of the battery. To evaluate the effectiveness of this approach, a real-world driving data-based test profile is employed. Moreover, a comparative analysis is conducted against recent state-of-the-art optimization algorithms. Simulation results demonstrate that the employed method is proficient in accurately and relatively quickly estimating the parameters of the ECM and surpasses other methods in terms of accuracy.

Keywords: Lithium-ion batteries; Equivalent circuit model; Rao-1 algorithm; Parameters extraction; Optimization

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1. Introduction

Lithium-ion batteries (LiBs) are currently a favored energy storage technology due to their remarkable advantages, including high energy density, low self-discharge rate, and exceptional cycle life. The availability of an accurate battery model is indispensable for effective Battery Management Systems (BMSs) and other renewable energy systems. Therefore, considerable research has been conducted to formulate sophisticated models aimed at precisely estimating the dynamic behaviors of LiBs [1]. Among the most versatile and accurate approaches capable of appreciating a wide range of battery scenarios and patterns are equivalent circuit models (ECMs) [2–4]. However, the process of parameterizing these models is critical for determining the battery's State of Charge (SoC) and state of health (SoH), and it can present several challenges.

Metaheuristic algorithms (MAs), which do not rely heavily on a multitude of designer-provided parameters, often drawing inspiration from the natural behavior of both biological and non-biological sources, are employed as powerful tools to address battery's parameter estimation challenges. In this context, researchers have offered diverse computational techniques to deal with the trouble of the ECMs parameter extraction.

As an illustration, the study in [5], researchers employed the Quantum Particle Swarm Optimization (QPSO) method to fine-tune unknown parameters within a simplified first-order fractional-order model (FOM). Similarly, Authors in [6] utilized the Honey Badger Algorithm (HBA) to estimate parameters in a data-driven model for a Vanadium Redox Flow Battery. Furthermore, recent advancements in the field of MAs have introduced innovative approaches, including the Artificial Ecosystem Optimizer (AEO) [7], the

Cuckoo Search (CS) [8], the Artificial Hummingbird Optimizer Technique (AHOT) [9], the Bald Eagle Search algorithm (BES) [10], and the COOT algorithm (COOT) [11], all of which have been utilized to extract parameters from battery ECMs.

In this study, we aim to investigate the application of the Rao-1 technique for parameter identification in LIB models based on the electrical ECM. In fact, several works have employed the Rao-1 method of estimation of transmission line parameters [12], parameter extraction in photovoltaic cell models [13], and various other research domains. However, to the best of our knowledge, the application of the Rao-1 method for identifying ECM parameters in lithium batteries has not been undertaken yet.

To assess the efficacy of the Rao-1 methodology, a test profile based on real-world driving data [14] is employed as an optimization framework. Furthermore, a comparative analysis is executed in contrast to contemporary optimization algorithms, specifically, Arithmetic Optimization Algorithm (AOA) [15], Harris Hawks Optimization (HHO) [16], Leader Harris Hawks Optimization (LHHO) [17] and Chernobyl Disaster Optimizer (CDO) [18]. Simulation outcomes substantiate that the Rao-1 technique excels in its ability to accurately and relatively rapidly estimate parameters inherent to the ECM and surpasses alternative methods.

2. Materials and Methods

2.1. Equivalent Circuit Model (ECM) for Li-ion battery

In this study, our emphasis revolves around the optimization of parameters within the extended Thevenin model, a model recognized for achieving a good equilibrium between precision and complexity. Illustrated in **Error! Reference source not found.**, this model takes the form of a second-order (2RC) model, denoting the presence of two RC branches sequentially aligned with the internal ohmic resistance R0 and the Voltage source (Voc). The adopted model encompasses a pair of state equations ((1) and (2)) and a singular output equation (3) [19] outlined as follows:

$$S\dot{O}C = -\frac{\eta}{Q_C} i_{bat}, \tag{1}$$

$$\dot{v}_i = -\frac{1}{R_i C_i} v_i + \frac{1}{C_i} i_{bat} \tag{2}$$

$$v_{bat} = V_{oc}(SOC) - R_0 i_{bat} - \sum_{i=1}^{i=2} v_i, \tag{3}$$

Where SOC is the State of Charge, Q_C is the battery nominal capacity (Ah), η is coefficient of charging, i_{bat} is the output/input current, v_{bat} is the terminal voltage, v_i denotes the voltage of the consistent RC branch, i is the branch number, and R_i and C_i are resistance and capacitor of the corresponding RC branch.

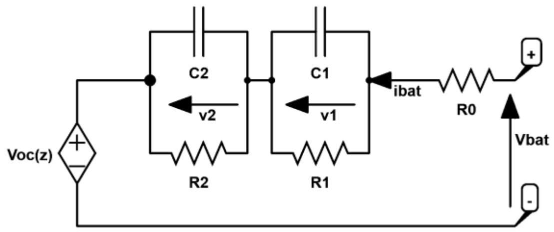

Figure 1. Schematic of the extended Thevenin (second-order) battery model.

For easier use in an optimization algorithm, ordinary differential equations (ODEs) of 2RC model could be converted from continuous time representation to discrete-time ODEs [20]. Hence, a final discrete-time expression, i.e. Eq. (4), will be considered in this paper.

$$v_{bat}[k] = V_{oc}(SOC[k]) - R_0 i_{bat}[k] - \sum_{i=1}^{i=2} v_i[k] \tag{4}$$

To include the battery dynamics differences between charging (indicated by "c") and discharging (indicated by "d") regimes, equation (4) was slightly modified as follows:

$$v_{bat}[k] = V_{oc}(SOC[k]) - R_{0c} i_c[k] - \sum_{i=1}^{i=2} v_{ic}[k] - R_{0d} i_d[k] - \sum_{i=1}^{i=2} v_{id}[k] \tag{5}$$

The non-linear relationship between the V_{oc} and SOC can be expressed as a sixth order polynomial exponential function [21]:

$$V_{oc} = a_0 + a_1 SOC + a_2 SOC^2 + a_3 SOC^3 + a_4 SOC^4 + a_5 SOC^5 + a_6 SOC^6 \tag{6}$$

Here, a_0 to a_6 are the polynomial coefficients.

2.2. Rao-1 Algorithm

The Rao-1 is a simple and recent metaphor less algorithm, that do not include any specific or complex parameters, updates the current solutions to converge toward the global solution using the following formula:

$$Y_{i,j}^{new} = Y_{i,j}^{t} + a_{1,j} \times \left(Y_{b,j}^{t} - Y_{w,j}^{t}\right) \tag{7}$$

where $j \in [1 \text{ Dim}]$ is the j^{th} dimension (Dim) of the i^{th} solution (noted by $Y_{i,j}^{t}$) during the current iteration t. $a_{1,j}$ is a random number selected from the interval $[0\ 1]$. The best and the worst solutions are denoted by $Y_{b,j}^{t}$ and $Y_{w,j}^{t}$, respectively. Finally, equation (7) is used to determine the value of the i^{th} solution in the coming iteration.

$$\begin{cases} Y_i^{t+1} = Y_i^{new}; if\ f(Y_i^{new}) < f(Y_i^{t}) \\ Y_i^{t+1} = Y_i^{t}; else \end{cases} \tag{8}$$

2.3. Objective function

Based on the LiB model descripted before, it can be concluded that different unknown parameters (i.e., $R_{0c}, R_{1c}, R_{2c},, C_{1c}, C_{2c}, R_{0d}, R_{1d}, R_{2d},, C_{1d}, C_{2d}, a_0$-$a_6$) are involved in the battery model. To closely match the real battery behavior, it's essential to accurately identify these 17 parameters. This identification is based on a real-world driving dataset with the actual current profile depicted in Error! Reference source not found. [14]. Hence, Rao-1 is used to estimate and optimize these parameters using this experimental dataset. The Root Mean Square Error (RMSE) was selected as an objective function to find proper parameters by effectively minimizing the error between the estimated (V_{est}) and experimental (V_{exp}) terminal voltages. Consequently, the objective function (F_{RMSE}) based on the RMSE formula is given by:

$$F_{RMSE}(x) = Min\left\{\sqrt{\frac{1}{N}\sum_{i=1}^{N}[V_{exp}(i) - V_{est}(i)]^2}\right\} \tag{9}$$

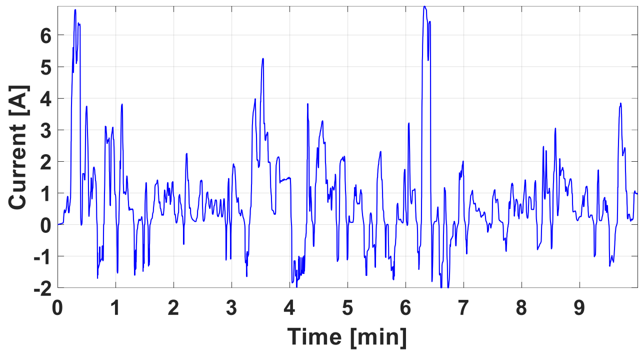

Figure 2. Current profile of the real world driving Dataset.

3. Results

In this subsection, we present a succinct summary of the optimization results obtained through the novel Rao-1 technique applied to the studied Lithium-ion Battery (LiB). The outcomes derived from the Rao-1 algorithm are systematically evaluated alongside the results obtained from four competing algorithms, namely AOA [15], HHO [16], LHHO [17] and (CDO) [18]. To ensure a fair and consistent comparison, all these techniques have been implemented within the MATLAB software environment, employing identical testing conditions. These conditions include a fixed number of iterations (MaxIt=100), a consistent population size (PopSize=30), and the execution of 10 independent runs for each method to uphold the reliability of the comparative analysis.

Table 1. illustrates the achieved parameters, along with their corresponding RMSE values for both the Rao1 approach and its counterpart methods. Remarkably, the lowest RMSE value ($4{,}3428 \times 10^{-3}$) with a Std of $2{,}1852 \times 10^{-3}$ was accomplished by the Rao1 technique which proves the good stability and accuracy the this algorithm. Error! Reference source not found. illustrates the estimated battery voltage plotted using the best parameters obtained by Rao-1 method. Clearly, the estimated curve can reduplicate the experimental data with a high precision.

Table 1. Optimal parameters acquired by Rao-1 and the other competitive algorithms.

Items	Rao-1	AOA	HHO	LHHO	CDO
R_{0d}	2,5911E-02	2,7995E-02	3,2126E-02	2,5178E-02	2,7906E-02
R_{0c}	3,5487E-02	2,8551E-02	3,1999E-02	3,9332E-02	2,4125E-02
R_{1d}	7,0652E-03	1,0000E-04	1,0076E-04	1,1627E-02	8,6901E-03
R_{1c}	1,0000E-01	6,4655E-02	2,9843E-02	5,1134E-02	8,3717E-02
C_{1d}	6,2604E+02	8,8250E+02	5,7939E+00	7,0488E+02	9,0000E+02
C_{1c}	3,6262E+02	9,0000E+02	3,6243E+02	8,8082E+02	2,9654E+02
R_{2d}	4,9927E-02	3,2199E-02	6,5794E-02	1,8990E-02	5,4462E-02
R_{2c}	3,6745E-02	3,2037E-02	2,0816E-02	7,9016E-02	5,4139E-02
C_{2d}	6,4907E+03	9,0000E+03	2,7513E+03	8,8490E+03	9,0000E+03
C_{2c}	5,9332E+03	9,0000E+03	4,6047E+03	8,8377E+03	5,2192E+03
a_0	3,2173E+00	4,0000E+00	3,6869E+00	3,3351E+00	3,2068E+00
a_1	1,0000E+00	1,9418E-02	4,2354E-01	8,5170E-01	1,0000E+00
a_2	-1,0000E-02	0,0000E+00	-3,8256E-03	-9,9321E-03	0,0000E+00
a_3	6,6396E-04	5,5631E-11	7,7382E-04	7,9015E-04	7,7291E-04
a_4	-1,0000E-04	0,0000E+00	-7,9211E-05	-3,0875E-05	0,0000E+00
a_5	1,0000E-05	4,6992E-19	2,1822E-06	3,3216E-06	8,6717E-06
a_6	-2,0351E-08	0,0000E+00	-4,3267E-08	-6,8963E-08	-8,3801E-11
Min RMSE	4,3428E-03	1,3183E-02	1,1558E-02	6,1840E-03	5,9515E-03
Std	2,1852E-03	8,3725E-04	6,7700E-03	4,5411E-03	5,6756E-03

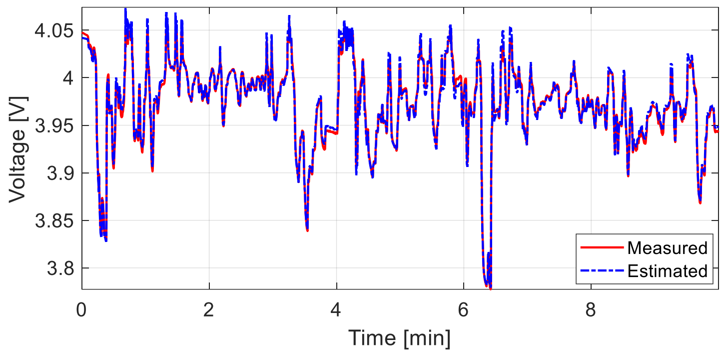

Figure 3. Measured and estimated LIB voltage via the Rao-1 algorithm.

Additionally, a visualization of the convergence curves generated by different algorithms is showcased in **Error! Reference source not found.**. Evidently, this illustration further validates the computational effectiveness and accuracy demonstrated by the Rao-1 algorithm, as it attains the optimal RMSE value by the 80th iteration.

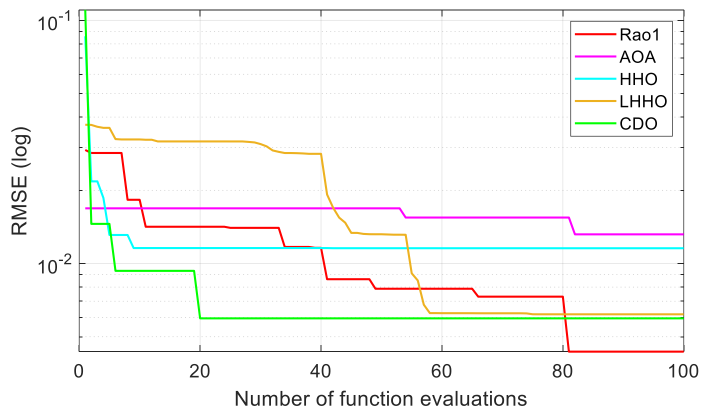

Figure 4. Convergence graphs for all implemented algorithms.

5. Conclusion

The aim of this paper is to evaluate the performance of the newly introduced Rao-1 algorithm in identifying the unknown parameters for battery's Equivalent Circuit Model. The algorithm is constructed based only on arithmetic operation and do not include any specific or complex parameters. The Rao-1 approach was examined using high accuracy experimental data, and the achieved results demonstrated the effectiveness and reliability of the proposed method compared to other optimization approaches for parameter estimation of LiBs. This algorithm accomplished a minimum RMSE, with a few number of iteration, of 4,3428 $\times$ 10^{-3} and Std of 2,1852 $\times$ 10^{-3}, representing high accuracy and robustness in predicting the battery voltage comportment. Besides, with the high closing between the calculated and the real characteristic, Rao-1 approach can be used as an efficiency tool for battery management systems.As a response to concerns about the potential impact of changing battery parameters on SOC estimation, we have proactively considered strategies to address this challenge. Our research leveraged real-world data to capture the actual operating conditions faced by Li-ion batteries, enhancing the algorithm's adaptability. Additionally, we recommend periodic recalibration of the battery model to align it with the evolving characteristics. Continuous monitoring and feedback mechanisms can further enhance accuracy over time.As we move forward, we look to further explore and refine the Rao-1 algorithm and other prominent metaheuristic algorithms. We aim also to integrate them into battery management systems taking into account crucial factors such as temperature, aging, and other significant variables. This approach contributes to more efficient and reliable energy storage solutions.

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References

1. Tian, H.; Qin, P.; Li, K.; Zhao, Z. A Review of the State of Health for Lithium-Ion Batteries: Research Status and Suggestions. *J. Clean. Prod.* 2020.
2. Merrouche, W.; Trari, M.; Djellal, L.; Mammeri, M.; Tebibel, H.; Blaifi, S.; Chong, L.W.; Ould-amrouche, S.; Boussaha, B. Improved Model and Simulation Tool for Dynamic SOH Estimation and Life Prediction of Batteries Used in PV Systems. *Simul. Model. Pract. Theory* **2022**, *119*, 102590, doi:10.1016/j.simpat.2022.102590.
3. Sepasi, S.; Ghorbani, R.; Liaw, B.Y. Improved Extended Kalman Filter for State of Charge Estimation of Battery Pack. *J. Power Sources* **2014**, doi:10.1016/j.jpowsour.2013.12.093.
4. Sepasi, S.; Ghorbani, R.; Liaw, B.Y. A Novel On-Board State-of-Charge Estimation Method for Aged Li-Ion Batteries Based on Model Adaptive Extended Kalman Filter. *J. Power Sources* **2014**, *245*, 337–344, doi:10.1016/j.jpowsour.2013.06.108.
5. Solomon, O.O.; Zheng, W.; Chen, J.; Qiao, Z. State of Charge Estimation of Lithium-Ion Battery Using an Improved Fractional-Order Extended Kalman Filter. *J. Energy Storage* **2022**, doi:10.1016/j.est.2022.104007.
6. Liu, Y.; Li, R.; Xiong, B.; Zhang, S.; Zhang, X.; Iu, H.; Fernando, T. A Novel Vanadium Redox Flow Battery Modelling Method Using Honey Badger Optimization Assisted CNN-BiLSTM. *J. Power Sources* **2023**, *558*, 232610, doi:10.1016/J.JPOWSOUR.2022.232610.
7. Ferahtia, S.; Djeroui, A.; Rezk, H.; Chouder, A.; Houari, A.; Machmoum, M. Optimal Parameter Identification Strategy Applied to Lithium-ion Battery Model. *Int. J. Energy Res.* **2021**, *45*, 16741–16753, doi:10.1002/er.6921.
8. Duru, K.K.; Venkatachalam, P.; Karra, C.; Madhavan, A.A.; Sambasivam, S.; Kalluri, S. Equivalent Circuit Model Parameters Estimation of Lithium-Ion Batteries Using Cuckoo Search Algorithm. *J. Electrochem. Soc.* **2022**, *169*, 120503, doi:10.1149/1945-7111/ACA6A5.
9. Hamida, M.A.; El-Sehiemy, R.A.; Ginidi, A.R.; Elattar, E.; Shaheen, A.M. Parameter Identification and State of Charge Estimation of Li-Ion Batteries Used in Electric Vehicles Using Artificial Hummingbird Optimizer. *J. Energy Storage* **2022**, *51*, 104535, doi:10.1016/j.est.2022.104535.
10. Ferahtia, S.; Rezk, H.; Djerioui, A.; Houari, A.; Motahhir, S.; Zeghlache, S. Modified Bald Eagle Search Algorithm for Lithium-Ion Battery Model Parameters Extraction. *ISA Trans.* **2023**, *134*, 357–379, doi:10.1016/J.ISATRA.2022.08.025.
11. Houssein, E.H.; Hashim, F.A.; Ferahtia, S.; Rezk, H. Battery Parameter Identification Strategy Based on Modified Coot Optimization Algorithm. *J. Energy Storage* **2022**, *46*, 103848, doi:10.1016/j.est.2021.103848.
12. Shoukat, A.; Mughal, M.A.; Ahmad, S.; Gondal, S.Y.; Khan, S.S. Parameter Estimation of Short Transmission Line Using Rao-I Algorithm. In Proceedings of the IMTIC 2021 - 6th International Multi-Topic ICT Conference: AI Meets IoT: Towards Next Generation Digital Transformation; 2021.
13. Benghanem, M.; Lekouaghet, B.; Haddad, S.; Soukkou, A. Optimization of Pv Cells/Modules Parameters Using a Modified Quasi-Oppositional Logistic Chaotic Rao-1 (QOLCR) Algorithm. *Environ. Sci. Pollut. Res.* **2023**, doi:10.1007/s11356-022-24941-2.
14. Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital Twin for Battery Systems: Cloud Battery Management System with Online State-of-Charge and State-of-Health Estimation. *J. Energy Storage* **2020**, *30*, 101557, doi:10.1016/j.est.2020.101557.
15. Abualigah, L.; Diabat, A.; Mirjalili, S.; Abd Elaziz, M.; Gandomi, A.H. The Arithmetic Optimization Algorithm. *Comput. Methods Appl. Mech. Eng.* **2021**, doi:10.1016/j.cma.2020.113609.
16. Heidari, A.A.; Mirjalili, S.; Faris, H.; Aljarah, I.; Mafarja, M.; Chen, H. Harris Hawks Optimization: Algorithm and Applications. *Futur. Gener. Comput. Syst.* **2019**, *97*, 849–872, doi:10.1016/J.FUTURE.2019.02.028.
17. Naik, M.K.; Panda, R.; Wunnava, A.; Jena, B.; Abraham, A. A Leader Harris Hawks Optimization for 2-D Masi Entropy-Based Multilevel Image Thresholding. *Multimed. Tools Appl.* **2021**, *80*, 35543–35583, doi:10.1007/s11042-020-10467-7.
18. Shehadeh, H.A. Chernobyl Disaster Optimizer (CDO): A Novel Meta-Heuristic Method for Global Optimization. *Neural Comput. Appl.* **2023**, doi:10.1007/s00521-023-08261-1.
19. Gregory L. Plett *Battery Management Systems: Equivalent-Circuit Methods*; 2016; ISBN 9781630810276.
20. Plett, G.L. *Battery Management Systems, Volume I: Battery Modeling*; Artech, 2015; Vol. 1; ISBN 9781630810245.
21. Hu, X.; Li, S.; Peng, H.; Sun, F. Robustness Analysis of State-of-Charge Estimation Methods for Two Types of Li-Ion Batteries. *J. Power Sources* **2012**, *217*, 209–219, doi:10.1016/j.jpowsour.2012.06.005.