# Robust parameter determination approach based on red-tailed hawk optimization used for lithium-ion battery

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**ABSTRACT**

Lithium-ion electrochemical batteries are being used more in a large number of applications, such as electric vehicles. However, increasing their efficiency lies in the accuracy of their model. For this, extracting the best values of parameters of the battery model is needed. A recent metaheuristic optimizer named the red-tail hawk (RTH) is used in the current research to extract the battery parameters. The idea of this algorithm is extracted from hunting techniques of red-tail hawks. The RTH algorithm is more likely to avoid entangled local optimums because of its high diversity, fast convergence rate, and appropriate exploitation-exploration balance. The RTH optimizer is compared with other algorithms to check and approve its performance. Using the proposed method, the root mean squared error (RMSE) between the model outputs and the measured voltage dataset was decreased to 8.12E-03, much better than all the other considered algorithms.



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## 1. INTRODUCTION

Being the prominent energy storage solution, batteries hold great promise in bringing the rapidly expanding intelligent grid idea and electric transportation systems to fruition. This potential lies in their capacity to store substantial energy for prolonged periods. Lithium-ion batteries are often chosen for electric vehicles due to their extended lifespan, and rapid charging attributes [1]-[3]. Multiple battery models were developed to simulate the battery behavior [4]. These models include mathematical representations, electrochemical simulations, and electrical circuit equivalents [5]. The capacity, efficiency, and runtime of batteries are predicted using mathematical models grounded in stochastic approaches or empirical equations [6]. Using resistance-capacitances (RCs) in series and parallel, similar circuit models provide high accuracy and require nothing in the way of parametrization work [7]. Some of these models are listed in Table 1.

Accurate modeling of Li-ion batteries (LIB) under various operating situations is essential to forecasting and simulated their behavior accurately. The Shepherd model is a macroscopic model that describes the battery's electrical behavior, including the voltage and the state of charge. However, these systems exhibit ongoing degradation starting from their initial use [1], leading to changes in their internal characteristics. Consequently, it is imperative to determine their internal parameters to assess their overall health [8], [9].

Table 1. Real battery parameters

| Category | Description | Model | Reference |
|---|---|---|---|
| Electrochemical models | Rooted in the electrochemical aspect of the battery components | Doyle fuller Newman (DFN) | [10] |
| | | Single particle model (SPM) | [11] |
| | | Pseudo-two-dimensional (P2D) | [12] |
| Equivalent circuit models (ECMs) | Approximative models designed to describe battery outputs | Shepherd model | [13] |
| | | RC models | [14], [15] |

In this context, the literature has proposed a variety of identification approaches. Using a group-wise approach, Shen and Li [16] suggested a method for identifying the parameters of LIBs. However, the effectiveness of this strategy depends on both the precision of the measurements and the availability of the data, as it is mostly exploratory. Researchers used an extended Kalman filter (EKF) and an unscented Kalman filter (UKF) to try to identify the resistance-capacitance (RC) model [17]. The accuracy of these methods depends on the filter selections, which may increase estimate inaccuracy. As reported in [18], the parameters of the Thevenin battery model are often identified using the H-infinity filter. A significant disadvantage of the aforementioned approaches is their dependence on the designer-supplied parameters.

Recently, intelligent and straightforward identification algorithms based on metaheuristic optimizers to extract the battery parameters have been widely employed to boost this trend further [13]. Electrochemical battery model parameters were obtained by employing a genetic algorithm (GA), as reported in [14]. The proposed model is founded on an established single-particle framework, which incorporates the solid-electrolyte-interface and is called enhanced single-particle (eSPM). In study [15], a variety of metaheuristic algorithms were used to estimate battery parameters using ECMs, including well-established techniques like the genetic algorithm (GA), particle swarm optimization (PSO), salp swarm algorithm (SSA), firefly algorithm (FA), grey wolf optimizer (GWO), multi-verse optimization (MVO), and whale optimization algorithm (WOA). Jusoh and Daud [19] utilized GA, PSO, and gravitational search algorithms (GSA) to identify the optimal Shepherd model set of parameters. Unfortunately, while the findings obtained using GA were the most beneficial, the associated error function had a significant size, resulting in decreased accuracy in parameter identification. As described in [20], parameter identification in the context of a lower-order model based on electrochemical models was carried out utilizing a mix of spectral techniques, a Kalman filter, and an ant lion optimizer. Initially, spectral techniques for simplification were used to simplify the electrochemical model. Then, a square-root cubature Kalman filter was applied for estimating the state, and finally, the ant lion optimizer was used to carry out parameter optimization. The study [21] extracted parameters for a Li-ion Shepherd model using an artificial ecosystem optimizer (AEO), producing positive results. Additionally, the modified COOT (mCOOT) algorithm was used in a similar investigation that was described in [22].

It is well known that metaheuristic optimization algorithms can provide sufficient solutions when used to extract a lithium-ion battery's parameters. However, they cannot guarantee the exact solutions due to their stochastic nature. For this reason, the researchers have used various optimization algorithms to solve this problem, where each algorithm can provide different results at different times. These research articles aim to extract solutions as close to the exact solutions as possible, with higher accuracy and similar or close results each time. The proposed method aims to provide better results in these terms compared to other published works. The proposed method is based on a recent meta-heuristic algorithm, the red-tail hawk (RTH) optimization algorithm [23]. The way red-tail hawks hunt is an inspiration for RTH. The RTH was inspired by the bald eagles' food-related seeking and hunting techniques. There are three phases in the RTH algorithm: the high soaring, the low soaring, and then the stooping and swooping phases. The RTH is applied to optimally get the battery parameters of a Shepherd model. The obtained results are compared with other optimizers including PSO [24], COOT [25], dandelion optimizer (DO) [26], equilibrium optimizer (EO) [27], GWO [28], osprey optimization algorithm (OOA) [29], sine cosine algorithm (SCA) [30], and SSA. The principal contributions of the suggested work are: i) Use the RTH for the first time for the battery parameters extraction problem, ii) Evaluating the performance of the proposed technique compared to other well-known metaheuristic optimization algorithms (MAs), iii) Accurately extract the Li-ion battery model parameters.

The paper is arranged as follows: section 2 describes the problem statement, including the battery model, the cost function, and its constraints. Section 3 reviews the RTH algorithms. Section 4 shows and discussed the obtained results. Where section 5 outlines the main findings.

## 2. PROBLEM STATEMENT

### 2.1. Battery modeling

Models of lithium-ion batteries have been developed by researchers all across the world [31]. These models include mathematical representations, electrochemical simulations, and electrical circuit equivalents

[5]. Batteries' capacity, efficiency, and runtime are predicted using mathematical models grounded in stochastic approaches or empirical equations [6]. Using RCs in series and parallel, similar circuit models provide high accuracy and require nothing in the way of parametrization work [32]. The Shepherd model, as explained previously, can reproduce the electrical behavior of the battery. Figure 1 presents the battery model using the Shepherd circuit. Consistent with [12], the battery voltage can be calculated.
Discharge model ($i^{*}> 0$):

$$V_{Bat} = E_0 - K\frac{C_B}{C_B - it}it - R_b i_{Bat} + A_b e^{(-B\times it)} - K\frac{C_B}{C_B - it}i^{*} \quad (1)$$

Charge model ( $i^{*} < 0$):

$$V_{Bat} = E_0 - K\frac{C_B}{C_B - it}it - R_b i_{Bat} + A_b e^{(-B\times it)} - K\frac{C_B}{it + 0.1C_B}i^{*} \quad (2)$$

where $E_0$ denotes open-circuit voltage, $C_B$ denotes the rating of the battery, $i_{bat}$ denotes the battery, $it$ is charging current, $i^{*}$ is the filtered battery current, $R_b$ represents the resistance, $A_b$ denotes exponential zone amplitude. The following relation can be used to express the battery's polarization resistance:

$$Pol_{res} = K\frac{C_B}{it + 0.1C_B} \quad (3)$$

Following are some rough calculations for the battery's state of charge (SOC):

$$SoC(t) = SoC_0 - \frac{1}{C_B}\int i_{Bat}dt \quad (4)$$

where $SoC_0$ denotes the initial SoC.

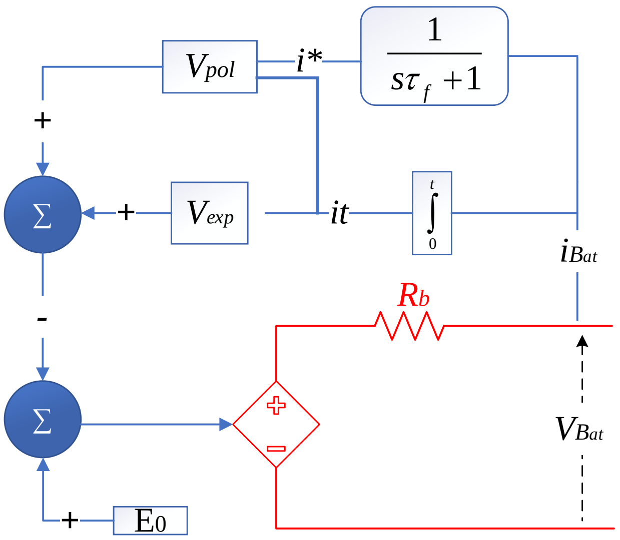


Figure 1. Li-ion battery model

### 2.2. Cost function formulation

The proposed identification method focuses on reducing the voltage differential as much as possible between the battery's actual data and its model. The voltage error serves as the input for the generation of the cost function. The root mean squared error (RMSE) objective functions are expressed as (5).

$$f(N) = \sqrt{\frac{1}{k}\sum_{N=1}^{k}\left(V_{Data}(N) - V_{Model}(N)\right)^2} \quad (5)$$

where $V_{Data}$ is the experimental data, $V_{Model}$ is the generated data by the Shepherd model, and $k$ is the data size.

The aim is to define the unknown model parameters by minimizing the cost function.

$$x = [E_0, R_b, C_b, K, A, B, \tau] \tag{6}$$

In the first stage, the algorithm assigns random values considering the following boundary limits.

$$lb \leq x \leq ub \tag{7}$$

where *lb* and *ub* are the upper and lower limits. Then, the error between the measured data and calculated data is determined, and the new positions are modified. This procedure will remain up until the optimal solution is obtained. The identification strategy can be illustrated in Figure 2.

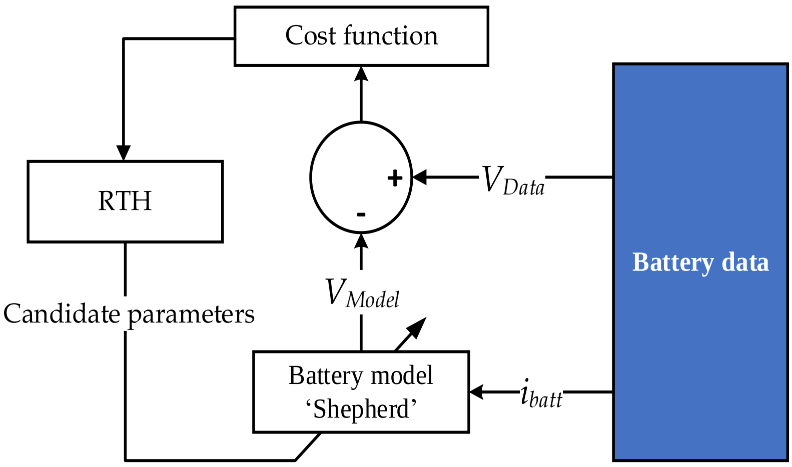


Figure 2. The proposed identification strategy

## 3. RED-TAILED HAWK OPTIMZATION

RTH is a type of bird of prey. Its hunting strategies inspired the RTH algorithm, a metaheuristic optimization method [23]. From the first step of prey identification to the last stage of swooping, the red-tailed hawk employs a methodical hunting approach. There are three phases to the hunting procedure:

- The hawk intensively scans the search area during the high-soaring stage, detecting prospective areas where its prey may be located. The mathematical equation of this stage can be presented as (8):

$$x_t = x_{best} + (x_{avr} - x_{t-1}).Lf.TF_t \tag{8}$$

  where, $x_t$ is the position of the hawk at iteration *t*, while $x_{best}$ is the best-attained position. $x_{avr}$ is the average position. *Lf* is the levy flight distribution, and $TF_t$ is the transition factor *t*.
- The hawk fine-tunes its motions inside the chosen zone surrounding the prey's location as it transitions to the low-soaring stage, deliberately determining the best locations for the approaching hunt. The mathematical equation of this stage can be presented as (9):

$$x_t = x_{best} + (dx_t - dy_t).(x_t - x_{avr}) \tag{9}$$

  where $dx_t$ and $dy_t$ represent directional coordinates during iteration *t*.
- The red-tailed hawk conducts a quick and accurate assault while stooping and swooping stage, effectively striking its victim with its swooping action.

$$x_t = a_t x_{best} + dx_t(x_t - TF_t x_{avr}) + dy_t(G_t x_t - TF_t x_{best}) \tag{10}$$

  where $G_t$ stands for the gravitational influence, which decreases as the hawk gets closer to the prey in an effort to reduce exploitation diversity, and $\alpha_t$ stands for the hawk's acceleration, which increases as *t* advances to speed up the convergence rate.

## 4. RESULTS AND DISCUSSION

Using MATLAB/Simulink, the simulation of a Shepherd model of the considered LIB will be produced. Within the constraints of the search space, proposals were created at random and then allocated to the model. After running the model using these variables, we compared the output to the already collected data. The ECE-15 urban driving cycle current profile has been considered. The exact numbers for the proposed battery's attributes are displayed in Table 2. Figure 3(a) and (b) present the produced voltage and the imposed current during the test.

Table 2. Actual parameters of the battery

| Parameter | $\boldsymbol{Q}$ | $R_{int}$ ($10^{-3}$) | $K$ ($10^{-3}$) | $B$ | $\tau$ | $E_0$ | $A$ |
|---|---|---|---|---|---|---|---|
| Actual value | 1500 | 1.8667 | 1.3985 | 0.040708 | 20 | 303.6205 | 23.5133 |

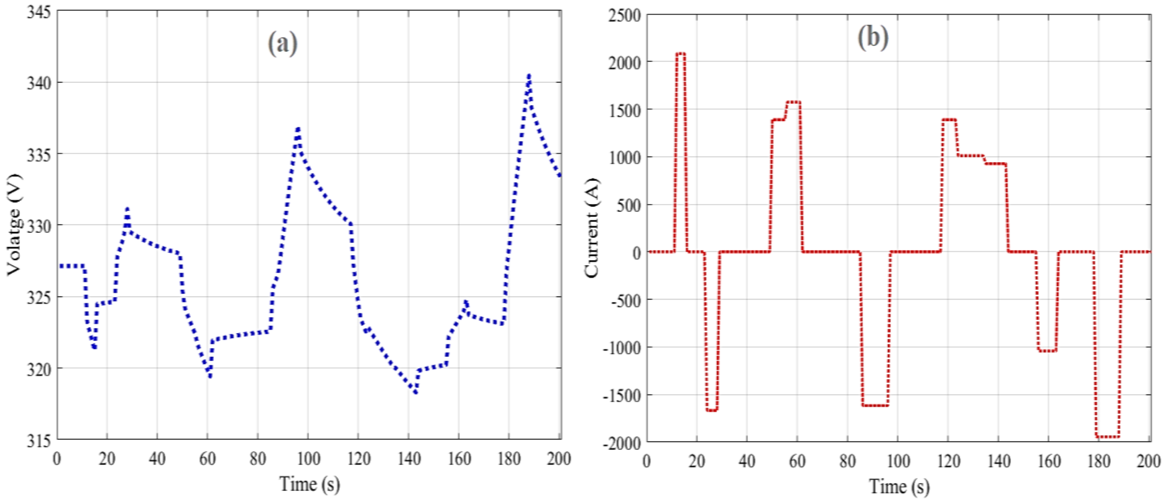


Figure 3. The battery (a) voltage and (b) current

Since the MAs are stochastic algorithms, each run has variable beginning positions. Statistical tests such as analysis of variance (ANOVA) and Tuckey might be utilized to evaluate robustness by contrasting the suggested method's performance with that of numerous MAs, including PSO, COOT, DO, EO, GWO, OOA, SCA, and SSA. Because MAs are inherently random, we tested each approach ten times to ensure their correctness and dependability. The population size is 30, the maximum number of iterations is 50 iterations, and the upper search space boundary is set at 120% of the real value, where the lower search space boundary is 80%. Table 3 displays the identification results of each run, Table 4 presents the statistical results, whereas the best-achieved results are presented in Table 5.

Considering Table 4, the best cost function values are ranged between 8.12E-03 and 1.54E-02. The maximum cost function of 8.12E-03 is obtained by RTH, followed by 8.72E-03 (using COOT), whereas the lower performance is obtained by SCA (1.54E-02). The average cost function values ranged between 8.37E-03 and 4.12E-02. The lowest value of 8.37E-03 is obtained by RTH, followed by EO (1.09E-02). SCA obtains the highest value of 4.12E-02. The standard deviation values range between 2.30E-04 and 1.20E-02. The lowest STD value of 2.30E-04 is obtained by RTH, followed by EO (3.32E-03). SCA obtains the highest STD value of 1.20E-02. The cost function evolution is shown in Figure 4, which shows that the proposed identification technique based on the RTH achieves better than others regarding convergence speed and final fitness value.

Table 6 presents a comprehensive comparison between the optimizers using the ANOVA test. The results definitively affirm the differences between the algorithms. In parallel, Figure 5 offers a graphical representation of the rankings, confirming the exceptional stability and accuracy demonstrated by the RTH algorithm. Figure 6 shows the outcomes of the Tukey post-hoc statistical test outcomes, which supports the ANOVA analysis findings. All the other optimizers' mean results significantly differ from those provided by the RTH. This confirms its excellent performance for this application.

The predicted voltage and SoC using each algorithm are shown in Figure 7 and the real data profile. The calculated values for the measured voltage profiles are almost exactly the same as those measured using the RTH. The EO also performed well; however, the RTH performed better based on the previous numerical analysis. The identification accuracy was validated by comparing the model output with the measurement data. As a result, proper identification will increase battery lifetime and improve battery management.

Considering the results in Table 4, RTH has best results in comparison with other used optimizers in terms of best (8.12E-03), worst (8.80E-03), mean (8.37E-03), and STD (2.30E-04). This approved its performance in solving the problems considered in this paper compared to the algorithms used. The proposed identification strategy 'RTH' results have been better than those of other published results recently for similar conditions. The RTH can be compared to the mBES [33] and SaBO [8]. Regarding best results, the RTH best value is 8.12E-03, whereas the mBES and SaBO best results are 8.12E-03 and 8.350e-03, respectively. Regarding worst values, the mBES and SaBO results are 42.180e-03 and 9.070e-03, whereas the RTH achieved 8.80E-03. Regarding the mean value, the RTH value is 8.37E-03, where the mBES and SaBO results are 21.340e-03 and 8.640e-03, respectively. This proves that the RTH performs better in solving the battery parameters extraction problem.

Table 3. Details of 30 runs

| | PSO | COOT | DO | EO | GWO | OOA | SCA | SSA | RTH |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.03E-02 | 8.73E-03 | 1.48E-02 | 9.28E-03 | 1.59E-02 | 3.49E-02 | 3.70E-02 | 2.66E-02 | 8.41E-03 |
| 2 | 1.49E-02 | 1.64E-02 | 1.29E-02 | 9.36E-03 | 2.65E-02 | 3.14E-02 | 2.92E-02 | 1.99E-02 | 8.32E-03 |
| 3 | 1.98E-02 | 1.21E-02 | 1.92E-02 | 9.43E-03 | 1.57E-02 | 3.04E-02 | 4.26E-02 | 1.95E-02 | 8.15E-03 |
| 4 | 1.45E-02 | 1.91E-02 | 1.37E-02 | 1.28E-02 | 1.85E-02 | 2.87E-02 | 4.09E-02 | 1.43E-02 | 8.24E-03 |
| 5 | 1.30E-02 | 1.36E-02 | 1.34E-02 | 8.79E-03 | 2.36E-02 | 2.64E-02 | 4.17E-02 | 2.03E-02 | 8.72E-03 |
| 6 | 1.63E-02 | 1.35E-02 | 9.58E-03 | 1.06E-02 | 2.13E-02 | 2.82E-02 | 4.38E-02 | 1.43E-02 | 8.12E-03 |
| 7 | 2.49E-02 | 1.51E-02 | 1.61E-02 | 1.98E-02 | 1.37E-02 | 3.13E-02 | 2.95E-02 | 1.60E-02 | 8.41E-03 |
| 8 | 1.27E-02 | 1.24E-02 | 9.48E-03 | 1.00E-02 | 1.51E-02 | 2.21E-02 | 1.54E-02 | 1.48E-02 | 8.12E-03 |
| 9 | 1.82E-02 | 9.67E-03 | 1.14E-02 | 1.20E-02 | 1.89E-02 | 2.02E-02 | 4.60E-02 | 2.34E-02 | 8.72E-03 |
| 10 | 1.55E-02 | 1.12E-02 | 8.90E-03 | 9.10E-03 | 2.72E-02 | 4.58E-02 | 6.07E-02 | 1.89E-02 | 8.19E-03 |
| 11 | 1.57E-02 | 1.17E-02 | 3.05E-02 | 1.09E-02 | 3.21E-02 | 3.21E-02 | 4.95E-02 | 1.87E-02 | 8.54E-03 |
| 12 | 1.53E-02 | 2.49E-02 | 1.12E-02 | 8.86E-03 | 1.96E-02 | 1.49E-02 | 4.00E-02 | 2.84E-02 | 8.80E-03 |
| 13 | 2.05E-02 | 1.10E-02 | 1.37E-02 | 1.28E-02 | 3.36E-02 | 1.34E-02 | 3.29E-02 | 2.51E-02 | 8.13E-03 |
| 14 | 1.39E-02 | 1.27E-02 | 1.44E-02 | 1.04E-02 | 3.32E-02 | 3.95E-02 | 6.59E-02 | 1.56E-02 | 8.35E-03 |
| 15 | 1.60E-02 | 1.18E-02 | 1.61E-02 | 9.29E-03 | 1.93E-02 | 3.66E-02 | 4.15E-02 | 1.53E-02 | 8.41E-03 |
| 16 | 1.42E-02 | 8.72E-03 | 9.36E-03 | 9.29E-03 | 2.22E-02 | 2.45E-02 | 3.09E-02 | 1.50E-02 | 8.67E-03 |
| 17 | 1.86E-02 | 8.79E-03 | 1.95E-02 | 1.12E-02 | 3.63E-02 | 2.83E-02 | 3.27E-02 | 2.65E-02 | 8.12E-03 |
| 18 | 1.28E-02 | 1.53E-02 | 1.44E-02 | 1.00E-02 | 2.18E-02 | 2.77E-02 | 4.22E-02 | 1.79E-02 | 8.37E-03 |
| 19 | 1.89E-02 | 1.00E-02 | 1.52E-02 | 9.05E-03 | 2.48E-02 | 2.75E-02 | 5.64E-02 | 1.58E-02 | 8.33E-03 |
| 20 | 1.28E-02 | 1.22E-02 | 1.39E-02 | 1.00E-02 | 4.03E-02 | 1.83E-02 | 2.58E-02 | 2.20E-02 | 8.72E-03 |
| 21 | 1.72E-02 | 1.04E-02 | 1.95E-02 | 1.09E-02 | 1.79E-02 | 2.60E-02 | 2.48E-02 | 2.21E-02 | 8.71E-03 |
| 22 | 1.60E-02 | 1.55E-02 | 1.21E-02 | 9.43E-03 | 2.51E-02 | 2.01E-02 | 5.76E-02 | 1.45E-02 | 8.12E-03 |
| 23 | 2.46E-02 | 1.51E-02 | 1.04E-02 | 8.69E-03 | 2.09E-02 | 3.64E-02 | 4.31E-02 | 2.81E-02 | 8.20E-03 |
| 24 | 2.89E-02 | 1.01E-02 | 1.31E-02 | 9.59E-03 | 3.59E-02 | 2.66E-02 | 5.14E-02 | 1.17E-02 | 8.12E-03 |
| 25 | 1.37E-02 | 1.28E-02 | 1.52E-02 | 9.33E-03 | 3.43E-02 | 1.97E-02 | 5.45E-02 | 3.41E-02 | 8.36E-03 |
| 26 | 2.87E-02 | 1.50E-02 | 1.33E-02 | 9.17E-03 | 2.59E-02 | 2.17E-02 | 2.08E-02 | 1.50E-02 | 8.21E-03 |
| 27 | 1.51E-02 | 1.17E-02 | 1.71E-02 | 2.35E-02 | 2.08E-02 | 2.53E-02 | 3.21E-02 | 2.93E-02 | 8.13E-03 |
| 28 | 2.53E-02 | 9.76E-03 | 1.37E-02 | 9.01E-03 | 2.38E-02 | 1.87E-02 | 5.41E-02 | 2.27E-02 | 8.12E-03 |
| 29 | 1.54E-02 | 2.26E-02 | 1.94E-02 | 1.64E-02 | 1.78E-02 | 3.17E-02 | 5.01E-02 | 2.65E-02 | 8.77E-03 |
| 30 | 1.45E-02 | 1.38E-02 | 1.34E-02 | 8.49E-03 | 2.47E-02 | 3.34E-02 | 4.17E-02 | 1.63E-02 | 8.40E-03 |

Table 4. Optimal parameters and numerical statistics

| | PSO | COOT | DO | EO | GWO | OOA | SCA | SSA | RTH |
|---|---|---|---|---|---|---|---|---|---|
| Best | 1.03E-02 | 8.72E-03 | 8.90E-03 | 8.49E-03 | 1.37E-02 | 1.34E-02 | 1.54E-02 | 1.17E-02 | 8.12E-03 |
| Worst | 2.89E-02 | 2.49E-02 | 3.05E-02 | 2.35E-02 | 4.03E-02 | 4.58E-02 | 6.59E-02 | 3.41E-02 | 8.80E-03 |
| Mean | 1.73E-02 | 1.32E-02 | 1.45E-02 | 1.09E-02 | 2.42E-02 | 2.74E-02 | 4.12E-02 | 2.03E-02 | 8.37E-03 |
| STD | 4.72E-03 | 3.75E-03 | 4.19E-03 | 3.32E-03 | 6.96E-03 | 7.25E-03 | 1.20E-02 | 5.59E-03 | 2.30E-04 |

Table 5. Optimal parameters and numerical statistics

| | PSO | COOT | DO | EO | GWO | OOA | SCA | SSA | RTH |
|---|---|---|---|---|---|---|---|---|---|
| $C_b$ | 1583.16 | 1394.53 | 1264.47 | 1260.16 | 1296.16 | 1591.50 | 1635.41 | 1539.00 | 1200.00 |
| $R_b$ ($10^{-3}$) | 1.6623 | 1.6339 | 1.5765 | 1.6230 | 1.7086 | 1.7652 | 1.7724 | 1.7021 | 1.6134 |
| $K$ ($10^{-3}$) | 1.5513 | 1.4860 | 1.4719 | 1.4602 | 1.4353 | 1.4997 | 1.6410 | 1.5437 | 1.4533 |
| $B$ | 0.0489 | 0.0412 | 0.0428 | 0.0409 | 0.0486 | 0.0435 | 0.0449 | 0.0420 | 0.0489 |
| $\tau$ | 22.2542 | 21.3579 | 21.0360 | 20.9255 | 21.6059 | 22.5725 | 19.3005 | 21.6668 | 20.7405 |
| $E_0$ | 307.556 | 303.879 | 304.728 | 303.591 | 307.284 | 304.043 | 307.568 | 304.512 | 306.989 |
| $A$ | 19.531 | 23.254 | 22.387 | 23.556 | 19.840 | 23.292 | 18.811 | 22.555 | 20.153 |

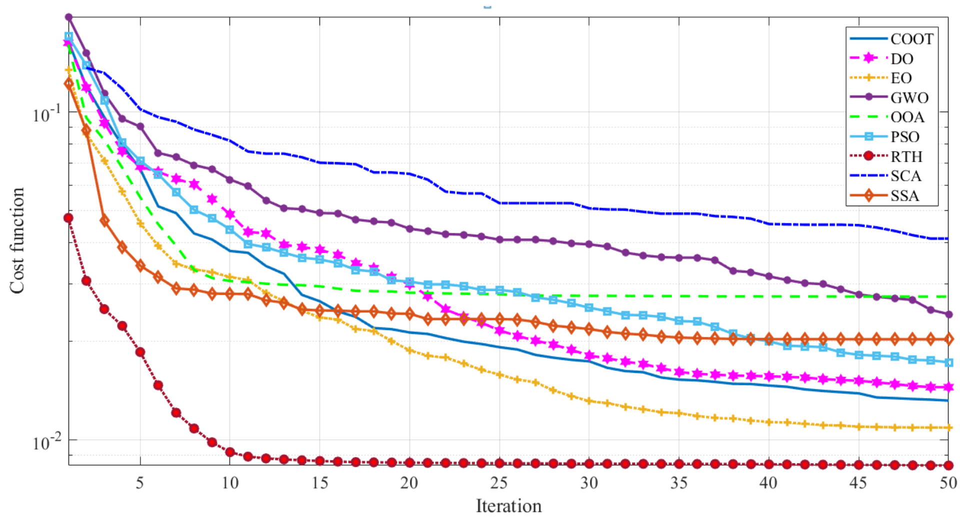


Figure 4. Average cost function using different optimizers

Table 6. ANOVA statistical test outcomes

| Source | df | SS | MS | F | Prob |
|---|---|---|---|---|---|
| Columns | 8 | 0.025 | 0.0031 | 78.3 | 6.06e-65 |
| Error | 261 | 0.010 | 0.0004 | | |
| Total | 269 | 0.035 | | | |

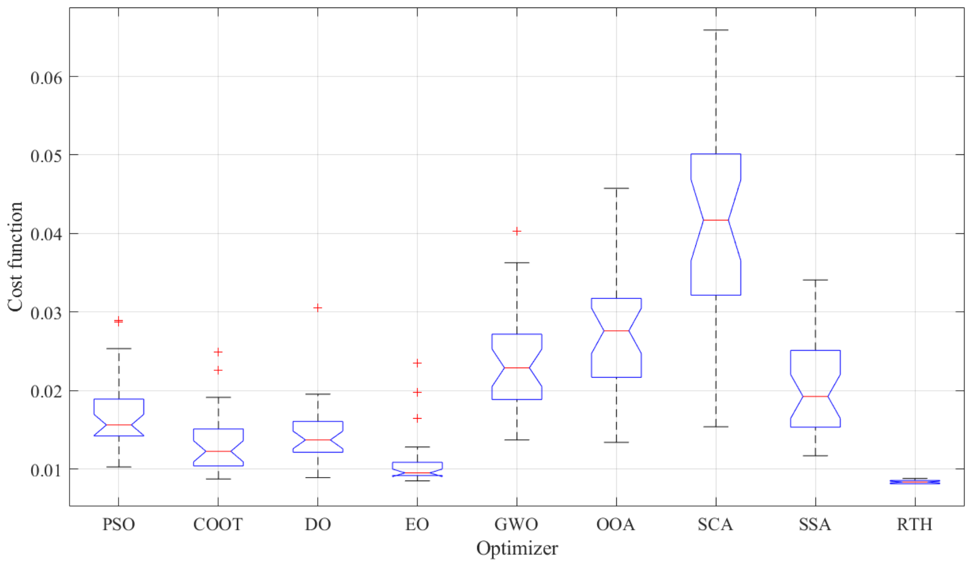


Figure 5. ANOVA graphical ranking

The primary target of this work is to present an identification method for lithium-ion battery parameter extraction with higher accuracy. The proposed methodology can extract the battery parameters with higher accuracy from the obtained results and after comparing them with other recently published papers. However, this may depend on the measured data and the used models. Microscopic models that can include the electrochemical and thermal aspects can be used to estimate the state of health better. However, macroscopic models like the one used are sufficient for energy management applications. Knowing the battery's actual parameters helps estimate its current state, which can help in battery management system design where the provided power depends on its actual capacity, as used in [33]. This can also help operate the battery in a comfortable condition, which can extend its lifecycle.

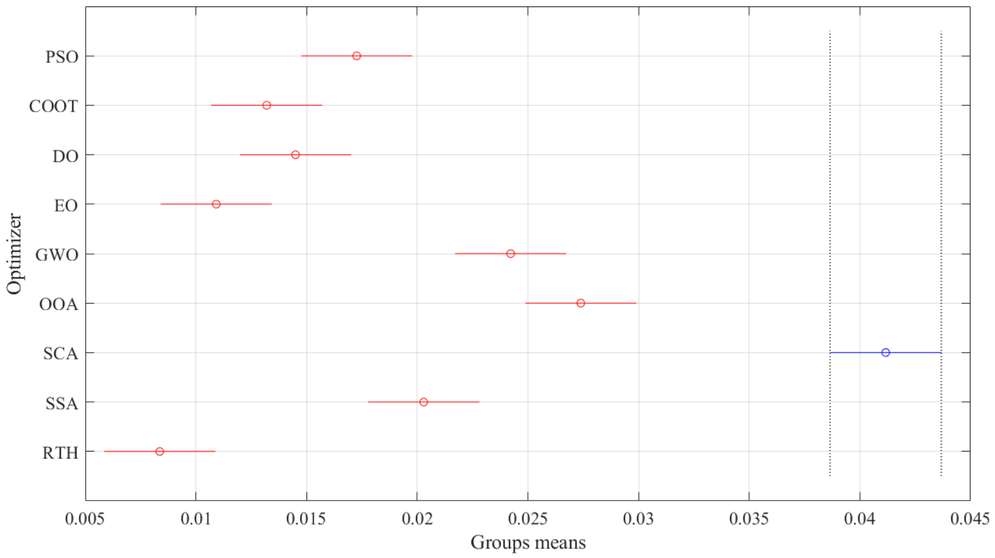


Figure 6. Tukey graphical ranking

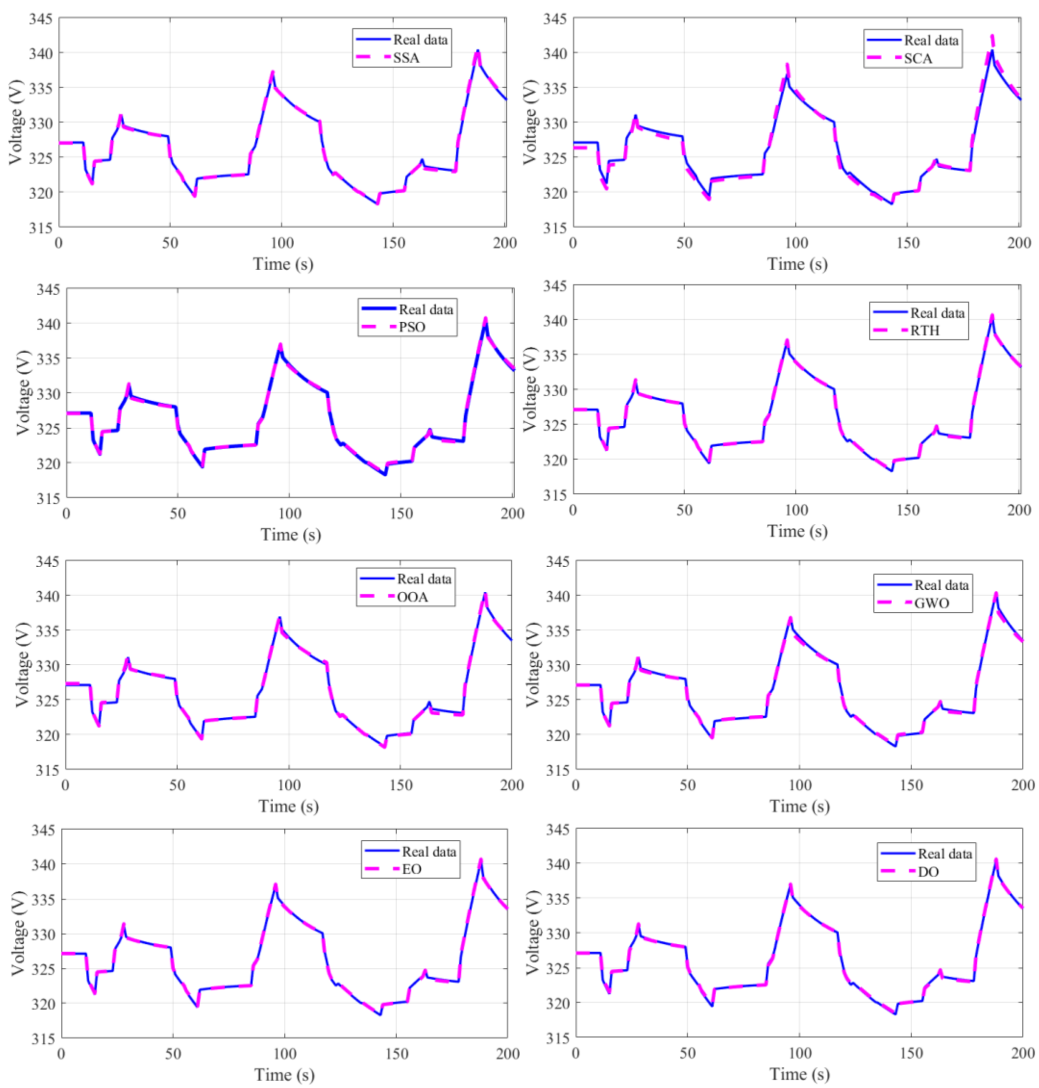


Figure 7. Estimated and measured for voltage waveforms

## 5. CONCLUSION

For the purpose of providing an efficient technique, this article makes use of the Red-tailed Hawk (RTH) algorithm, which is a relatively new metaheuristic methodology. The results of this study indicated an accurate identification method that was based on the RTH optimizer and offered outstanding performance for this application. By comparing the results of the proposed approach with those of other algorithms, such as PSO, DO, COOT, GWO, OOA, SCA, and SSA techniques, it has been shown that the recommended strategy produces accurate results. Following the completion of the identification process, the findings reveal that the RTH is advantageous when it comes to extracting the parameters of the battery. When contrasted with the other methods, the mean value of the cost function is 8.37E-03, while the EO comes in at 1.09E-02. In addition, the RTH yields the best result at 8.12E-03, followed by the EO at 8.49E-03, which is the best result produced altogether. Compared to the other algorithms, the RTH has extraordinary resilience, as shown by its standard deviation of the results is 2.30E-04, which is lower than that of the others. Find out what characteristics Li-ion batteries should have. The fundamental purpose of this investigation is to make a prediction about the real properties of the battery.

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