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Experimental and Theoretical Analysis of the Fast Charging Polymer Lithium-Ion Battery Based on Cuckoo Optimization Algorithm (COA)

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ABSTRACT Fast charging of the electric-vehicles is one of the paramount challenges in solar smart cities. This paper investigates intelligent optimization methodology to improvise the existing approaches in order to speed up the charging process whilst reducing the energy consumption without degradation in the light of the outrageous demand for lithium-ion battery in the electric vehicles (EVs). Two fitness functions are combined as the targeted objective function: energy losses (EL) and charging interval time (CIT). An intelligent optimization methodology based on Cuckoo Optimization Algorithm (COA) is implemented to the objective function for improving the charging performance of the lithium-ion battery. COA is applied through two main techniques: The Hierarchical technique (HT) and the Conditional random technique (CRT). The experimental results show that the proposed techniques permit a full charging capacity of the polymer lithium-ion battery (0 to 100% SOC) within 91 mins. Compared with the constant current-constant voltage (CCCV) technique, an improvement in the efficiency of 8% and 14.1% was obtained by the Hierarchical technique (HT) and the Conditional random technique (CRT) respectively, in addition to a reduction in energy losses of 7.783% and 10.408% respectively and a reduction in charging interval time of 18.1% and 22.45% respectively. Experimental and theoretical analyses are performed and are in good agreement on the polymer lithium-ion battery fast charging method.

INDEX TERMS Constant current-constant voltage (CCCV), cuckoo optimization algorithm (COA), electric vehicles (EV), electric vehicle fast charging, lithium-ion battery, RC second-order transient.

I. INTRODUCTION

The lithium-ion battery is becoming the backbone of most of the popular energy storage systems worldwide [1]. It is the infrastructure of the modern technologies such as Electric Vehicles (EV), plug-in hybrid vehicles (PHEV), Energy Storage Systems (ESS), and most of the portable electronics [1]. Recently, the lithium-ion battery is commercialized because of its wide voltage range, low charging rate, low self-discharging rate, long life cycle, and high energy efficiency [1]–[3]. Due to the dynamic characteristics and complex behavior of the lithium-ion batteries, knowledge of its various equivalent circuits models is an essential step to understand its performance [4]–[8].

Modeling of Lithium-ion batteries could be divided into two main categories: 1) the first category is Electrochemical model that describes the electrochemical reaction occurring in the battery [7], and 2) the second category is its electronic equivalent circuit that is based on the characteristics of the lithium-ion battery and can be branched into Rint model, PNGV model, Thevenin model, RC first-order transient model and RC second-order transient that is also called Dual Polarization (DP) model [9]–[13].

Studies are ongoing to achieve faster battery charging as the main drawbacks that face Lithium-ion batteries during charging are the slow charging rate, the unpredictable effect

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on the battery performance, and the energy loss [12]. The challenge is to speed up the battery charge without affecting its electrochemistry [14]. Charging strategies can be categorized into three main techniques: 1) pulse charging technique [12], 2) constant current-constant voltage (CCCV) technique, and 3) multi-stage charging current technique [15].

Pulse charging technique is mainly based on an appropriate selection of the current waveform parameters, however, the difficulty in choosing the appropriate parameters for pulses [12] and the very low switching duty cycle [16] could be considered as limitations. On the other hand, the constant current-constant voltage (CCCV) technique represents the standard charging method because of its easy implementation and simple requirements. CCCV methodology is based on charging the battery by a constant rated charging current until the voltage reaches the cut off value and then the voltage is held constant while the current decays to the minimum value. This causes an increase in the charging interval time, consequently, resulting in an unoptimized charging [12].

In multi-stage charging current technique, the battery is charged by a multi-stage of different currents and the lifetime extends without a degradation impact [12]. Many algorithms and techniques have been implemented for multi-stage constant current charging of the lithium-ion battery in Table 1 such as Particle Swarm Optimization (PSO) based Fuzzy Logic, Consecutive Orthogonal Arrays, Correcting Slope Iteratively, Taguchi Approach, Ant Colony algorithm (ACA), Optimal charge pattern (OCP), Balance of Internal Consumption and Charging Speed, Particle Swarm Optimization (PSO), Negative pulse, Boost-charging, and Dynamic programming algorithm.

Previous researchers used various methodologies to study the charging process, such as the type of model used, the charging time or/and the energy consumption, the charging efficiency performance, the charging capacity, and the no. of tests used, which are summarized in Table 1.

Meta-heuristic algorithms presented in the previous table such as Particle Swarm Optimization (PSO) [16], [17] and Ant Colony algorithm (ACA) [21] operate based on a combination between rules and mimic animal behavior in the natural environment. PSO simulates a bird predation behavior belongs to the swarm intelligence algorithm. The particles move in the search-space and communicate with the rest of the swarm during the exploration. ACA is inspired by the supervision of a real set of artificial cooperative ants that used pheromone deposited on graph edges in solving the problems and exchanging information [21]. Each algorithm has been used in Table 1 has its approach, objective function and own parameters included from the equivalent circuit model of the lithium-ion battery.

In this study, the analysis of several techniques based on the Cuckoo optimization algorithm (COA) to optimize the total energy consumption and battery charging interval time to reach the full capacity limit is obtained. COA has been

TABLE 1. Multi-stage constant charging current comparison between the proposed algorithm (cuckoo optimization algorithm (COA)) and other algorithms presented in the literature survey.

Method	Model	Tests	Stages	Charging Efficiency improvement	Charged capacity	Energy Loss Saved	Time Reduced
				compared to the constant current-constant voltage (CCCV) technique			
Particle Swarm Optimization (PSO) Based Fuzzy-Controlled [17]	N/A	112	5	0.4%	88%	N/A	56.8 %
Consecutive Orthogonal Arrays [18]	N/A	54	5	1.02%	95%	N/A	11.2 %
Correcting Slope Iteratively [19]	RC series equivalent circuit	N/A	N/A	N/A	N/A	N/A	N/A
Taguchi Approach [20]	N/A	54	5	0.68%	75%	N/A	62.3 %
Ant Colony algorithm (ACA) [21]	N/A	57	5	N/A	70%	N/A	N/A
Optimal charge pattern (OCP) [1,14]	RC series equivalent circuit	1	5	0.54%	100 %	1.8%	11.9 %
Balance of Internal Consumption and Charging Speed [15]	R circuit	N/A	N/A	N/A	80%	N/A	13.8 %
Particle Swarm Optimization (PSO) [16]	RC second-order Transient	N/A	14	N/A	70%	2.27 %	0%
Negative pulse [22]	RC second-order Transient	N/A	N/A	N/A	N/A	N/A	N/A
Boost-charging [23]	N/A	N/A	N/A	N/A	80%	N/A	N/A
Dynamic programming algorithm [24]	RC First order transient	N/A	N/A	N/A	95%	5.45 %	7.66 %

TABLE 1. *(Continued.)* **Multi-stage constant charging current comparison between the proposed algorithm (cuckoo optimization algorithm (COA)) and other algorithms presented in the literature survey.**

The hierarchical technique (HT)	RC second-order Transient	1	5	8%	100 %	7.783 %	18.1 %
The conditional random technique (CRT)				14.1%	100 %	10.408 %	22.45%

implemented using the second-order transient equivalent circuit model after measuring all the parameters.

II. LITHIUM-ION BATTERY EQUIVALENT CIRCUIT MODELLING

RC second-order transient equivalent circuit model (DP model) in Fig. 1 represents the transient behavior of the polymer lithium-ion battery. The DP model has proved to be the closest circuit model that can be used to explain the performance and behavior of lithium-ion batteries [4].

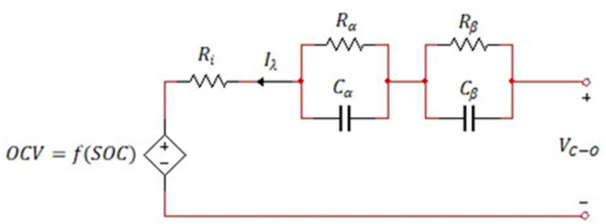

FIGURE 1. **The proposed RC second-order transient equivalent model of a lithium-polymer battery.**

The RC second-order transient model consists of three main sectors [25]–[28]: open circuit voltage OCV, which depends on the battery state of charge, internal resistances including the ohmic internal resistance (R_i), the electrochemical polarization internal resistance (R_α) and the concentration polarization internal resistance (R_β) and lastly, the internal capacitances such as the electrochemical polarization capacitance (C_α) and the concentration polarization capacitance (C_β).

The electrical behavior and relationship between the circuit components [26] and can be expressed as follow

$$I_{C_{\alpha_\lambda}} = I_\lambda \left\{ 1 - \frac{1 - e^{\frac{-\Delta t}{R_\alpha C_\alpha}}}{\frac{\Delta t}{R_\alpha C_\alpha}} \right\} + I_{\lambda-1} \left\{ \frac{1 - e^{\frac{-\Delta t}{R_\alpha C_\alpha}}}{\frac{\Delta t}{R_\alpha C_\alpha}} - e^{\frac{-\Delta t}{R_\alpha C_\alpha}} \right\} + I_{C_{\alpha_{\lambda-1}}} \left\{ e^{\frac{-\Delta t}{R_\alpha C_\alpha}} \right\} \quad (1)$$

$$I_{C_{\beta_\lambda}} = I_\lambda \left\{ 1 - \frac{1 - e^{\frac{-\Delta t}{R_\beta C_\beta}}}{\frac{\Delta t}{R_\beta C_\beta}} \right\} + I_{\lambda-1} \left\{ \frac{1 - e^{\frac{-\Delta t}{R_\beta C_\beta}}}{\frac{\Delta t}{R_\beta C_\beta}} - e^{\frac{-\Delta t}{R_\beta C_\beta}} \right\} + I_{C_{\beta_{\lambda-1}}} \left\{ e^{\frac{-\Delta t}{R_\beta C_\beta}} \right\} \quad (2)$$

where, I_λ is the total current of the present stage λ, $I_{C_{\alpha_\lambda}}$ is the stage current passes through the electrochemical polarization capacitance (C_α), $I_{C_{\beta_\lambda}}$ is the current passes through the concentration polarization capacitance (C_β) and Δt is the change in interval time.

The detailed calculations of the OCV and the internal parameters of the proposed polymer lithium-ion battery are explained in the following sections.

A. OPEN CIRCUIT VOLTAGE (OCV)- STATE OF CHARGE (SOC) METHOD

There are various methods to estimate SOC. The first method is the Open Circuit Voltage (OCV) which is used to measure the voltage at the required SOC percentage, however, precise relaxation time should be taken into consideration [29]–[31]. Secondly, the Coulombs Counting method that relies on the current integration is depending on a controlled sensor, however, a regular calibration should be done to avoid any error [32]–[37]. The last one is the machine learning method, which is based on the reliability of the collected data and includes the following: the artificial intelligent [38]–[40], the support vector machines algorithm (SVM) [41], [42] and the Kalman filter family methods that rely on the state-space model, however, the machine learning method has a poor performance in transients [43]–[49].

SOC with a low percentage of error is required to optimize the energy loss, the interval time required to charge the battery, safety usage, and battery management. The integration of the Coulomb Counting method represented in (3) with the OCV method has proved to cause no critical side effects during normal battery operation [25], [31], [35].

$$SOC_\lambda = SOC_{\lambda-1} \pm \left(\eta \times \frac{\int_{t_0}^{\tau} I_{\lambda-1}.d\tau}{C_{Rate}} \right) \times 100\% \quad (3)$$

where $\pm$ the positive sign for charging and negative sign for discharging, SOC_λ is the state of present charging stage λ, $I_{\lambda-1}$ is the current of the battery at stage $(\lambda - 1)$, η is the coulomb coefficient and it is constant $=1$ for discharging and $=0.98$ for charging and C_{Rate} is the rated capacity of the battery (Ah).

The procedures of SOC estimation using the integration between the coulomb counting method and the OCV method are presented in the flow chart of Fig. 2(a). The proposed procedures are implemented to draw the relationship between OCV compared to SOC at room temperature 25°C using NI myRIO-1900 as shown in Fig. 2(b).

B. INTERNAL PARAMETERS OF THE PROPOSED BATTERY MODEL

The values of the proposed battery equivalent circuit model have been calculated based on the battery terminal potential difference during the discharging current pulses. The discharging current pulses have been implemented in a short interval time of 20 s with a 600 s relaxation period before and after the applied current pulse [25], [27]. Fig. 3. shows specific voltages and times during the discharging pulses which are used to calculate the internal parameters of the lithium-polymer battery.

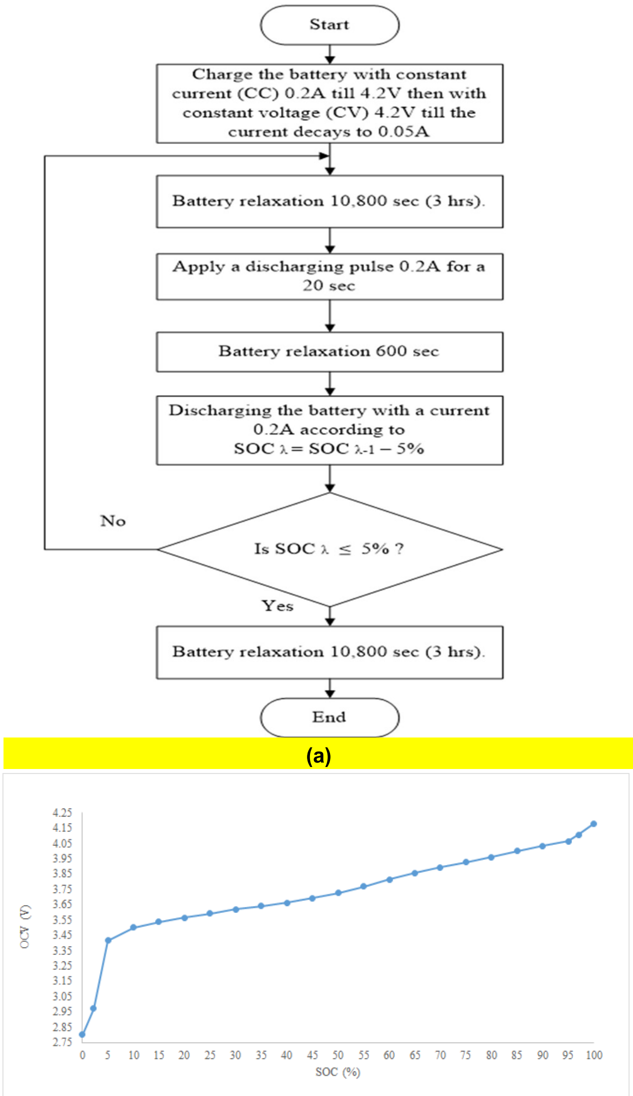

FIGURE 2. Illustrates (a) the procedures of the OCV-SOC test method and (b) the relation between OCV-SOC of the lithium-polymer battery cell at room temperature 25°C.

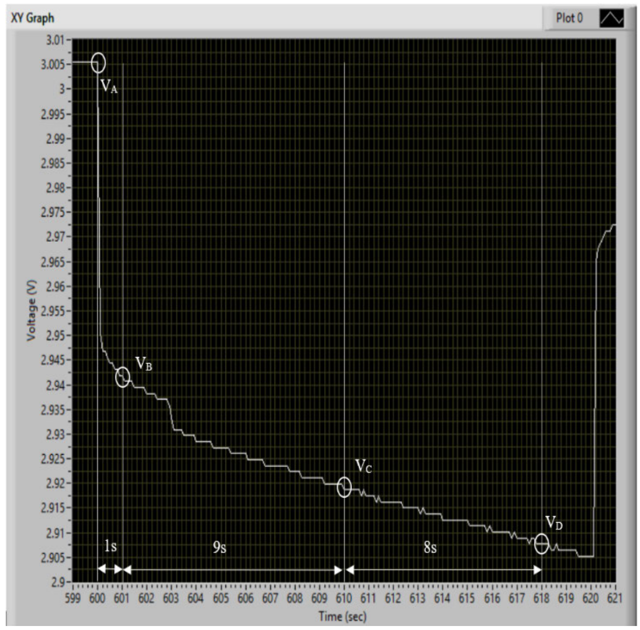

FIGURE 3. Discharging current pulse sample graph measured by NI myRIO during the interval time 20 s at room temperature 25°C.

By applying a discharging current pulse 0.2A on the used polymer lithium-ion battery, the ohmic internal resistance R_i, the electrochemical polarization internal resistance R_α and the concentration polarization internal resistance R_β have been calculated after 1 s, 10 s, and 18 s respectively [25]. The equations given in [26] have been used to calculate the internal resistances and capacitances and have been illustrated in the appendix. The relationship between the internal parameters of the proposed battery model and SOC are presented in Fig. 4.

III. DERIVATION AND LIMITATIONS OF THE FAST CHARGING FITNESS FUNCTION

A. DERIVATION OF THE FAST CHARGING FITNESS FUNCTION

To reach the battery's full capacity with a minimum charging interval time and energy consumption, an objective function (fitness function) should be minimized. The energy loss for the proposed RC second-order transient equivalent circuit can be expressed as follow

$$E.L.(J) = \sum_{\lambda=1}^{N}\Big[\Big\{I_\lambda^2 R_i T_\lambda\Big\} + \Big\{(I_\lambda - I_{C_{\alpha_\lambda}})^2 R_\alpha T_\lambda\Big\} + \Big\{(I_\lambda - I_{C_{\beta_\lambda}})^2 R_\beta T_\lambda\Big\}\Big] \quad (4)$$

where N is the total number of constant current charging stages and T_λ is the total time of current charging at the stage λ.

By considering the interval change in time of the system is $\Delta t = 1s$ and the change of SOC is $\Delta SOC = 1\%$, the charging interval time for each stage will be expressed as $T_\lambda\,(sec) = (36/I_\lambda)$ from (3).

The objective function intended in this study stated in (5) was obtained by using (1), (2), (3), and (4).

$$Min.Objective\ Function = \Bigg[\omega_1 \times \sum_{SOC_{\lambda-1}=1}^{SOC_\lambda}\sum_{\lambda=1}^{N}\Bigg[\Big\{I_\lambda^2 R_i \frac{36}{I_\lambda}.\Big\} + \Bigg\{\Bigg(I_\lambda\Bigg\{\frac{1-e^{\frac{-\Delta t}{R_\alpha C_\alpha}}}{\frac{\Delta t}{R_\alpha C_\alpha}}\Bigg\} - I_{\lambda-1}\Bigg\{\frac{1-e^{\frac{-\Delta t}{R_\alpha C_\alpha}}}{\frac{\Delta t}{R_\alpha C_\alpha}} - e^{\frac{-\Delta t}{R_\alpha C_\alpha}}\Bigg\} - I_{C_{\alpha_{\lambda-1}}}\Big\{e^{\frac{-\Delta t}{R_\alpha C_\alpha}}\Big\}\Bigg)^2 R_\alpha \frac{36}{I_\lambda}\Bigg\} + \Bigg\{\Bigg(I_\lambda\Bigg\{\frac{1-e^{\frac{-\Delta t}{R_\beta C_\beta}}}{\frac{\Delta t}{R_\beta C_\beta}}\Bigg\} - I_{\lambda-1}\Bigg\{\frac{1-e^{\frac{-\Delta t}{R_\beta C_\beta}}}{\frac{\Delta t}{R_\beta C_\beta}} - e^{\frac{-\Delta t}{R_\beta C_\beta}}\Bigg\}$$

$$-I_{C_{\beta_{\lambda-1}}}\left\{e^{\frac{-\Delta t}{R_\beta C_\beta}}\right\}\Bigg)^2 R_\beta \frac{36}{I_\lambda}\Bigg\}\Bigg]\Bigg]$$

$$+\left[\omega_2 \times \sum_{\lambda=1}^{N}\left(\frac{(SOC_\lambda - SOC_{\lambda-1}) * 36}{I_\lambda}\right)\right]\Bigg] \quad (5)$$

where ω_1 is the weighting factor of the total energy loss and it could be adjusted from 0 to 1 and ω_2 is the weighting factor of the total required charging interval time where $\omega_2 = 1 - \omega_1$.

B. LIMITATIONS OF FAST CHARGING ALGORITHMS

1) CUT OFF VOLTAGE OF EACH STAGE (V_{c-o_λ})

Every battery has a charging cut-off voltage which should not be exceeded to guarantee the battery from damage, overcharging and to ensure a better lifespan [23]. The proposed polymer lithium-ion battery should not exceed the maximum permitted voltage for each stage which can be expressed by $V_{c-o_\lambda} \leq 4.25$.

2) THE MAXIMUM PERMITTED CHARGING CURRENT OF EACH STAGE (I_{ξ_λ})

The charging current should not exceed a security threshold value. The security threshold value can be presented as a relationship between the charging constant current (0.05A - 1A) and the charging interval time [24]. To avoid the overcharging and the damage of the battery, the maximum permitted charging current that ensures the voltage of the charging battery does not exceed the cut-off voltage can be described as:

$$I_{\xi_\lambda} = \begin{cases} 1 & T_\lambda \leq 2,480\,\text{sec} \\ \dfrac{-T_\lambda}{6000} + 1.413 & T_\lambda > 2,480\,\text{sec} \end{cases} \quad (6)$$

where I_{ξ_λ} is the maximum permitted charging current for each stage and T_λ is the charging interval time of stage λ.

C. THE PROPOSED CUCKOO OPTIMIZATION ALGORITHM (COA)

Cuckoo Optimization Algorithm (COA) has been implemented on the proposed RC second-order transient equivalent circuit to determine the optimum charging interval time and the optimum energy loss during charging. COA is superior to various optimization algorithms (genetic algorithm, particle swarm, ant colony, …etc) for the multimodal objective functions due to the robust to dynamic changes and broad applicability [50]–[52].

Cuckoo Optimization Algorithm (COA) is inspired by the behavior life of a species of birds called Cuckoo. This technique is mainly the form of grown cuckoos and eggs. Grown cuckoos put their eggs in the nests of various birds as they have two probabilities: 1) the first is that the host bird kills the eggs, and 2) the second is that the eggs are not killed and recognized by the host bird and grow up and become a grown cuckoo [52], [53]. The cuckoo optimization algorithm tends

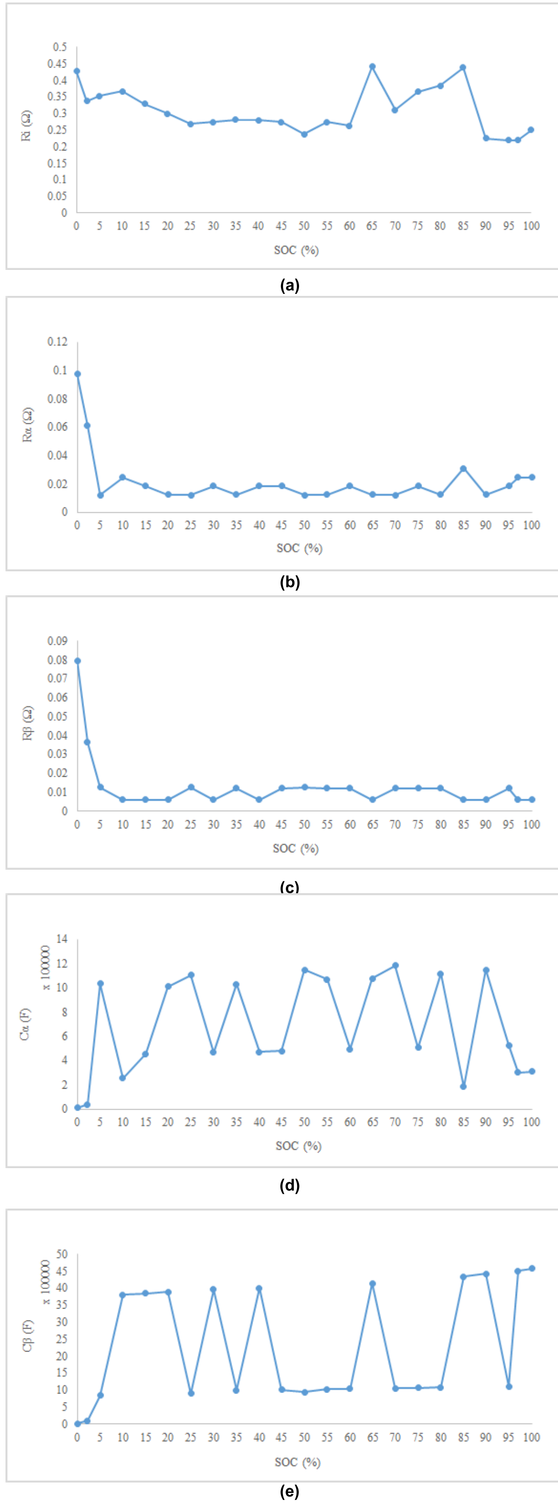

FIGURE 4. The relationship between the internal parameters of the proposed battery model (a) The ohmic internal resistance R_i, (b) The electrochemical polarization internal resistance R_α, (c) The concentration polarization internal resistance R_β, (d) The electrochemical polarization capacitance C_α and (e) The concentration polarization capacitance C_β corresponding to SOC during an interval discharging pulse 20 s at room temperature 25°C.

to find the best habitat for all cuckoos where there is a high opportunity for eggs to grow up. The best suitable habitat will be the target for cuckoos in other societies [52], [54].

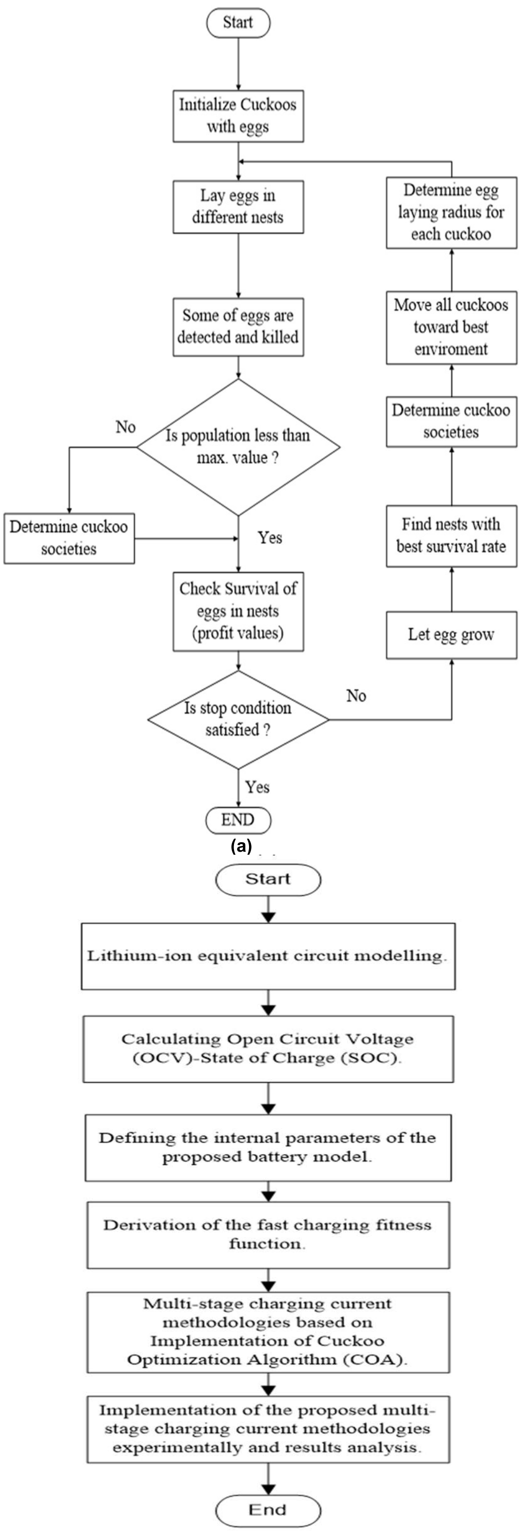

FIGURE 5. Presents (a) The flowchart of the cuckoo optimization algorithm (COA) and (b) The procedures performed to implement the proposed multi-stage charging current methodologies.

The procedures of using the proposed Cuckoo Optimization Algorithm (COA) are explained by the flowchart in Fig. 5(a) illustrating each step including the initial population (Cuckoo's Habitat), Laying Eggs Style, Immigration of Cuckoo, Eliminating Cuckoos, and the convergence criteria. Furthermore, the steps performed to implement the proposed multi-stage charging current methodologies are presented in Fig. 5(b).

IV. RESULTS AND DISCUSSION

A polymer lithium-ion battery has been selected as a test case. A detailed specification of this battery is given in Table 2.

TABLE 2. Specifications of the selected polymer lithium-ion battery.

Item	Specification
Type	Polymer lithium-ion battery
Nominal Capacity	1000 mAh
Maximum charging current	1C A
Maximum discharging current	2C A
Charging cut-off voltage	4.2 ± 0.05 V
Discharging cut-off voltage	2.75 V

Multi-stage fast charging methodologies have been implemented on the polymer lithium-ion battery to reach full capacity ($SOC_{\lambda} = 100\%$) as illustrated in Fig. 6, which can be categorized into two main scenarios: the first scenario is the standard CCCV methodology and the second scenario is Multi-Stage Charging Current methodology (MSCC) based on Cuckoo Optimization Algorithm (COA). COA is simulated using MATLAB (R2017a, The MathWorks Ltd, Natick, MA, USA).

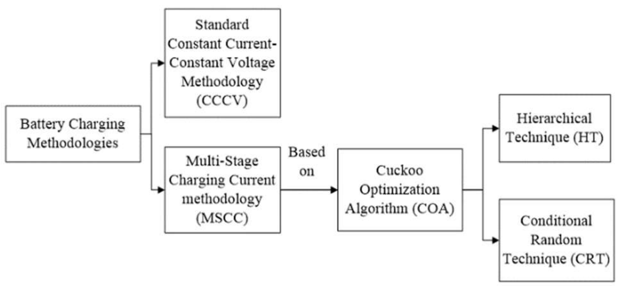

FIGURE 6. The proposed scenarios of charging the lithium-polymer battery.

A. CONSTANT CURRENT-CONSTANT VOLTAGE (CCCV) APPROACH

CCCV methodology is the standard technique for any battery charging. It is performed on the polymer lithium-ion battery by applying a constant current 1 A until the voltage reaches the cut-off value (4.25 V) and then the voltage is held constant while the current decays to the minimum value of 0.05 A. This methodology took 7,100 s (1.9722 h) till the battery reached its full capacity (0 to 100% SOC) of 4.1785V after a relaxation time 10,800 s (3 h) as shown in Fig. 7(a).

B. MULTI-STAGE CHARGING CURRENT BASED CUCKOO OPTIMIZATION ALGORITHM (COA)

Multi-stage charging current methodologies have been applied on the polymer lithium-ion battery, and it is divided into two main scenarios based on the conditional boundaries of the currents as follow:

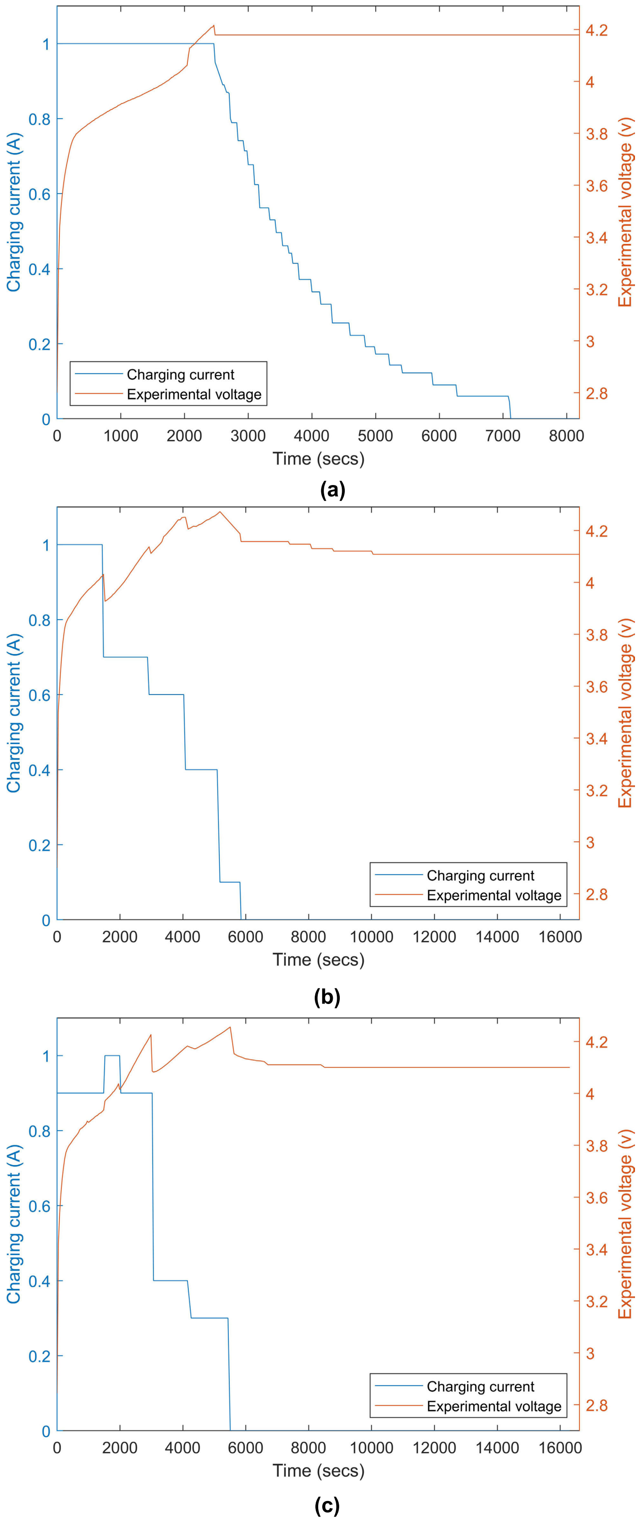

FIGURE 7. Relationship between different charging methodologies for polymer lithium-ion battery at room temperature 25°C (a) The standard CCCV methodology, (b) Multi-stage charging current methodology based on HT and (c) Multi-stage charging current methodology based on CRT.

1) HIERARCHICAL TECHNIQUE (HT)

The first scenario called Hierarchical Technique (HT) which has been obtained by applying a hierarchical stepping down variable constant currents during the charging process

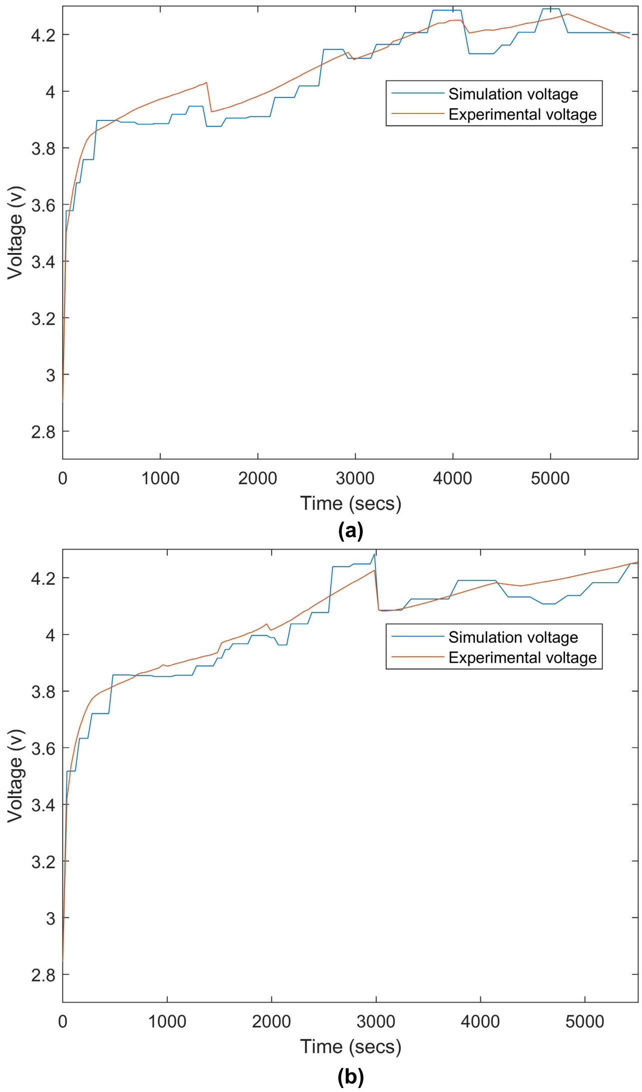

FIGURE 8. The maximum error declaration between experimental and simulated voltage results for both HT and CRT at room temperature 25°C respectively.

$I_\lambda \leq I_{\lambda-1}$ corresponding to the experimental measured voltage of the battery as presented in Fig. 7(b).

Based on the Hierarchical Technique (HT), the battery reached full capacity (0 to 100% SOC) in 5,815 s (1.6153 h) and based on the dynamic behavior and relaxation theory of batteries, the capacity of the battery reached 97% (4.107 V) after a relaxation time of 10,800 s (3 h).

By applying HT based on COA, the total energy consumed during the charging process was reduced by 7.783%, the total charging interval time was reduced by 18.1% and the efficiency was improved by 8% based on (7), (8) and (9) respectively compared to CCCV methodology test [17].

$$E_{Saved} = \frac{E.L._{CCCV} - E.L._{Propsed}}{E.L._{CCCV}} \times 100 \qquad (7)$$

$$T_{reduced} = \frac{T_{CCCV} - T_{Propsed}}{T_{CCCV}} \times 100 \qquad (8)$$

TABLE 3. A detailed comparison between the CCCV methodology and the proposed scenarios based on COA at room temperature 25°C.

	Standard CCCV Methodology	Cuckoo Optimization Algorithm (COA) Hierarchal Technique (HT)	Cuckoo Optimization Algorithm (COA) Conditional Random Technique (CRT)
I_1 (A)		1	0.9
I_2 (A)		0.7	1
I_3 (A)	1	0.6	0.9
I_4 (A)		0.4	0.4
I_5 (A)		0.1	0.3
T_1(s)		1,474	1,493
T_2(s)		1,451	484
T_3(s)	7,100	1,157	1,018
T_4(s)		1,096	1,264
T_5(s)		637	1,247
Total charging Time (s)	7,100	5,815	5,506
Energy Loss (J)	1,127.667	1,039.9	1,010.3

$$\eta_{improved} = \left(\frac{C_{dis_{proposed}}}{C_{ch_{propsed}}} - \frac{C_{dis_{CCCV}}}{C_{ch_{CCCV}}} \right) * 100 \tag{9}$$

where E_{Saved} is the energy saved, $T_{reduced}$ is the reduced charging interval time, $C_{dis_{proposed}}$ is the discharging capacity of the proposed technique, $C_{ch_{propsed}}$ is the charging capacity of the proposed technique and $\eta_{improved}$ is the improved efficiency of the proposed charging technique.

2) CONDITIONAL RANDOM TECHNIQUE (CRT)

The second scenario was based on the conditional randomness of the cuckoo optimization algorithm which chooses the values of the stage current lying within the boundaries declared in section 4 and presented in Fig. 7(c). The battery reached its full capacity (0 to 100% SOC) in 5,506 s (1.5294 h), but based on the dynamic behavior and relaxation theory of batteries, the capacity of the battery reached 97% after a relaxation time of 10,800 s (3 h). The energy consumption saved by the Conditional Random Technique (CRT) is 10.408 %, the time was reduced to 22.45 %, and the efficiency was improved by 14.1%.

The proposed previous two techniques improved the efficiency of the fast charging of the polymer lithium-ion battery with minimum energy loss and less interval time with respect to the previous data presented in the literature. The maximum error between the experimental and simulated voltage results of the two scenarios (HT and CRT) is presented in Fig. 8. The maximum error of the proposed RC second-order equivalent circuit model reached 2.3%. The maximum error between the experimental and simulated charging voltages has been calculated by:

$$\text{з}\,(\%) = \frac{\text{ɱ}_{Experiment} - \text{ɱ}_{Simulation}}{\text{ɱ}_{Experiment}} * 100 \tag{10}$$

where з is the percentage of error and $\text{ɱ}_{Experiment} - \text{ɱ}_{Simulation}$ is the difference between the maximum experimental and simulated voltage points respectively.

Detailed results obtained from the previous techniques include charging stage current, charging interval time for each stage, total charging time for all the process, and the total energy loss presented in Table 3. As shown, the proposed techniques based on COA and the simulation-based on the RC second-order transient circuit have a good impact on the interval time and the consumed energy of the charging process.

TABLE 4. The results of changing the weights of energy loss and charging interval time.

ω_1	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ω_2	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
I_1(A)	0.9	1.0	1.0	1	0.8	0.9	0.4	1.0	1.0	0.8	1.0
I_2(A)	1.0	0.7	0.7	0.8	1.0	1.0	0.9	0.9	0.7	1.0	0.8
I_3(A)	0.9	0.5	1.0	0.9	0.7	0.9	1.0	0.7	0.8	0.9	0.8
I_4(A)	0.6	0.1	0.7	0.6	0.4	0.4	0.8	0.6	0.7	0.6	0.3
I_5(A)	0.3	0.3	0.6	0.4	0.4	0.3	0.5	0.6	0.6	0.4	0.2
T_1(s)	602	1,500	420	1,255	915	1493	333	1479	574	1500	1500
T_2(s)	1,445	1,468	1145	1,076	1,435	484	874	474	1392	590	1438
T_3(s)	491	1,470	882	300	1,234	1,018	881	893	348	492	410
T_4(s)	1,219	893	1500	1,254	704	1264	1356	1299	1421	1217	1474
T_5(s)	1,443	440	803	1,231	619	1247	1404	490	1378	1486	1500
Time(s)	5,200	5,771	4,750	5,116	4,907	5,506	4,848	4,635	5,113	5,285	6,322
Energy Loss (J)	1,032	994.500	1,066.1	1,023.7	964.904	1,010.3	984.381	1,053	995.922	921.47	1,073.1

3) ANALYSIS OF THE WEIGHTING FACTORS

In furtherance of the foregoing, each weight of the energy loss and charging interval time changed in (5) to vary from 0 to 1 where $\omega_1 + \omega_2 = 1$. Any change in energy loss weight ω_1 or the charging interval time weight ω_2 will result in a different combination of five constant currents with different charging interval times based on COA as shown in Table 4.

Based on the relationship between the current of each stage, the interval time of each stage and the conditional constraints/boundaries, any change in the weight of energy loss or in the charging interval time will not affect the charging capacity based on COA.

COA rearranges the data and searches for the optimum solution to minimize energy loss and charging interval time based on the objective function regardless of the weighting factor as explained in Table 4.

V. CONCLUSION

An intelligent optimization technique based on the Cuckoo Optimization Algorithm (COA) was applied in this study. COA was implemented on an objective function used for the fast charging of the polymer lithium-ion battery with minimum energy consumption and minimum charging interval time. The proposed algorithm was applied to a dynamic model based on the RC second-order transient equivalent circuit. A comparison between two implemented techniques and CCCV methodology was performed yielding the following results: 1) Hierarchical Technique (HT) reached its full capacity (0 to 100% SOC), caused a reduction in both the charging interval time and energy loss by 18.1% and 7.783% respectively and improved the efficiency by 8 %, 2) Conditional Random Technique (CRT) reached its full capacity (0 to 100% SOC), caused a reduction in both the charging interval time and energy loss by 22.45% and 10.408% respectively and improved the efficiency by 14.1%. The maximum error between the proposed simulation model and the experimental work is 2.3%. The proposed techniques prove that whenever the weight of energy loss or charging interval time is changed, new currents and interval times will be regenerated to optimize the fitness function.

APPENDIX

The internal parameters of the proposed second-order transient equivalent circuit have been illustrated and calculated from [25], [27] as follow:

(a) The ohmic internal resistance R_i calculated just after 1 s of applying a discharging current pulse 0.2A. The values of ohmic internal resistance have been calculated by the immediate voltage and discharging current according to (1A) for each change in the state of charge $(\Delta SOC) = 5\%$

$$R_i = \frac{V_{BA} - V_B}{I_{Discharging}} \tag{1A}$$

(b) The electrochemical polarization internal resistance R_α has been calculated after 10 s of applying a discharging current pulse 0.2A. It depends mainly on the voltage difference within a short period of 9 s. The electrochemical polarization internal resistance has been measured for each change in the state of charge $(\Delta SOC) = 5\%$ by

$$R_\alpha = \frac{V_B - V_C}{I_{Discharging}} \tag{2A}$$

(c) The concentration polarization internal resistance R_β has been determined after 18 s of applying a discharging current pulse 0.2A for each change in the state of charge $(\Delta SOC) = 5\%$ by

$$R_\beta = \frac{V_C - V_D}{I_{Discharging}} \tag{3A}$$

(d) The electrochemical polarization capacitance C_α has been calculated by (4A) for each change of state of charge $(\Delta SOC) = 5\%$

$$C_\alpha = \frac{9I}{(V_C - V_B)\ln\left(\frac{V_C}{V_B}\right)} \tag{4A}$$

(e) The concentration polarization capacitance C_β has been calculated by (5A) for each change of state of charge $(\Delta SOC) = 5\%$

$$C_\beta = \frac{8I}{(V_D - V_C)\ln\left(\frac{V_D}{V_C}\right)} \tag{5A}$$

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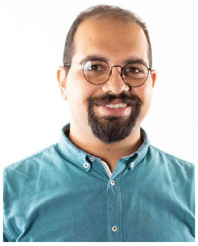

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