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(Research Article)

Firefly algorithm-based estimation of the dynamics of lithium-ion battery used in wireless sensors

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Abstract

Wireless sensors are powered by small-sized batteries with limited energy and lifespan; hence, proper battery management is essential for communication reliability and network performance. Thus, this paper presents a firefly algorithm (FA) – based model for estimating the battery's behaviour. A single resistor-capacitor (RC) circuit representing the battery was simulated to obtain the voltage response of the battery to charge and discharge current pulses. The battery was first fully charged, and discharge current pulse of 30 mA was applied for 5 seconds within a duration on one hour. The measured voltage responses were stored, and the procedure was repeated for each 10% State-of-Charge (SoC) interval until the battery was discharged. The transfer function of the circuit was transformed into coefficients that were optimized by the FA for estimating the terminal voltage, Open-Circuit Voltage (OCV) and SoC of the battery. The proposed FA model estimated the terminal voltage with an average estimation error of 8.2 mV. The FA model gave Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of 0.0479 and 0.0864, respectively, which outperforms the conventional Ampere-hour (Ah) Counting method that incurred MAE and RMSE of 0.1115 and 0.1361, respectively. The results reveal that the FA model outperforms the Ah Counting method in OCV-SoC estimation by 76.72 %. This study has shown that the proposed FA model is suitable for providing improved battery level estimation for wireless sensors; thus, Wireless Sensor Networks (WSN) can be better monitored and operated.

Keywords: Lithium-Ion; Firefly Algorithm; Wireless Sensor; Ampere Hour; State-Of-Charge (Soc); Battery Parameters

1. Introduction

Wireless sensor networks (WSNs) have revolutionized the field of communications for sensing functionality, alerting, enabling data collection, real-time monitoring applications (such as environmental, healthcare, disaster, machine) and industrial automation [1, 2]. The WSNs are the bedrocks of the Internet of Things (IoT) technology for collecting, transmitting, processing, analyzing, alerting and visualizing data on systems such as electricity grids to ensure data-process efficiency, providing the basis for alerts or signals in case of system related issues or errors [3, 4, 5].

A Wireless Sensor (WS) is powered by small-sized batteries with limited energy and lifespan; hence, proper battery management is essential for communication reliability and network performance [6]. There are mechanisms such as IEEE 802.15.4 protocol for estimating the on-line energy consumption of WSs [7]. Different classes of batteries such as alkaline, nickel, lithium-polymer and lithium-ion are employed in WS [6]. Over charging or over discharging shortens the lifespan of a rechargeable battery [8]. In consequence, a battery model useful for predicting the performance of the WS battery is of utmost importance for informed decision making such as energy harvesting [9, 10]. Furthermore, the parameters of a battery model depend on the internal states of the battery, and the factors that limit the development of optimal battery model for a given application are computational overhead, inadequate experimental data and the type of discharge profile [11, 12]. Battery model parameters such as voltage, capacity, load current and temperature variations are to be estimated during the operation of the battery [13].

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In this study, a computational intelligence approach using the Firefly Algorithm (FA) [14] was adopted in investigating the dynamics (or behaviour) of the lithium-ion (Li-ion) battery for a WS.

2. Related work

Battery modelling can be classified into four major approaches namely Analytical Model (AM), Electrochemical Model (EM), Equivalent Circuit Model (ECM), and Artificial or Computational Intelligence-Based Model (ACIM) [15, 16, 17].

The AM approach was adopted in [18]. An EM approach was proposed by Gao & Lu (2024) [19]. Studies on the ECM strategy were carried out in [20, 21, 22]. An ACIM approach using Recurrent Neural Network (RNN) for estimating the SoC of the Li-ion battery was investigated by Jerouschek et al. (2020) [23]. Another ACIM approach using Dynamic Time Warping (DTW) was developed by Rente et al. (2021) [24]. Hybridization of Radial Basis Function (RBF) and Gaussian Process Regression (GPR) was investigated in [6].

3. Material and methods

The section presents the methodology for developing the proposed FA-based battery model.

3.1. Generation of the Charge and Discharge Profile of the Battery

A single RC block was simulated in MATLAB/Simulink to obtain the voltage response of the Li-ion battery to charge and discharge current pulses. The discharge currents were adapted from [6] for the wireless sensor operating on the IEEE 802.15.4 protocol. The procedure for charging and discharging the battery to obtain the voltage response is presented in Figure 1. The procedure starts by charging the battery to 100% capacity. Then, beginning with the 10% of the initial SoC, the battery was discharged by injecting the discharged current pulse for 5 seconds. The voltage responses were stored, and the procedure was repeated for each 10% SoC interval until the battery was completely discharged. The capacity rate (C-rate) and discharge currents injected into the battery are 0.03C and 30 mA, respectively, at room temperature.

3.2. Derivation of the Battery’s Input-Output Relationship

The Li-ion battery for WS application is modelled as a single (n = 1) RC circuit in this study [25]. The battery’s internal characteristics can be described by the circuit diagram shown in Figure 2. Applying Kirchoff’s voltage law to the circuit gives the battery’s terminal (or output) voltage V_t at time t as:

$$V_t(t) = V_o(t) - V_B(t) - V_{drop}(t). \qquad \text{………………(1)}$$

with

$$V_{drop}(t) = I_B(t)R_o \qquad \text{…………….} \qquad (2)$$

where V_o is the open-circuit voltage (OCV), V_B is the voltage across the RC block, V_{drop} is the voltage drop,I_B is the battery’s current, R_B and C_B represent the diffusion process in the battery, and R_o is the ohmic resistance during instantaneous voltage drop.

Equation (1) can be expressed in the frequency domain by applying the Laplace transform to give:

$$V_t(s) = V_o(s) - \frac{I_B(s)R_B}{1+sR_BC_B} - I_B(s)R_o. \qquad \text{…………… (3)}$$

Re-arranging Equation (3) in terms of input-output relationship gives:

$$\frac{V_t(s)-V_o(s)}{I_B(s)} = -\left[\frac{R_B}{1+sR_BC_B} + R_o\right]. \qquad \text{………..(4)}$$

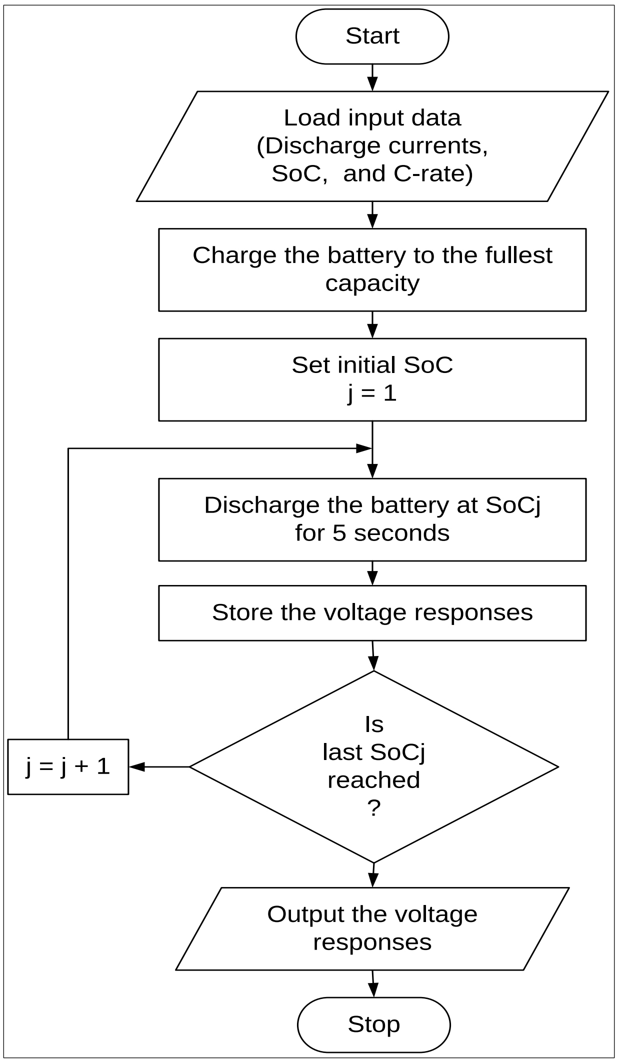

Figure 1 Charge and Discharge Process of the Battery

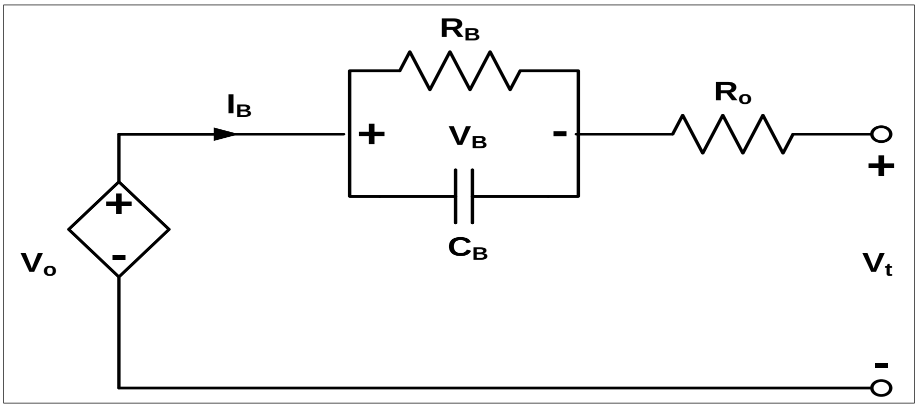

Figure 2 Single equivalent circuit model for the Li-ion battery

Thus, the transfer function $G(s)$ of the circuit can be expressed as:

$$G(s) = \frac{V_t(s) - V_o(s)}{I_B(s)} = -\left[\frac{sR_O + \frac{R_O + R_B}{R_B C_B}}{s + \frac{1}{R_B C_B}}\right] = -\frac{a_1 s + a_o}{b_1 s + b_o}. \quad \text{.......(5)}$$

The parameters R_o, R_B and C_B can be obtained by solving the polynomial coefficients

(a_o, a_1, b_o, b_1) of $G(s)$. Applying bilinear transformation [26, 27] to Equation (5) gives the equation in discrete time k as:

$$m_1\left(V_{t,k} - V_o\right) + m_2\left(V_{t,k-1} - V_o\right) = m_3 I_{B,k} + m_4 I_{B,k-1}\,. \quad \ldots\ldots\ldots\ldots\ldots \quad (6)$$

where

$$m_1 = \frac{2}{t} + \frac{1}{\tau_B}. \quad \ldots\ldots\ldots\ldots\ldots(7)$$

$$m_2 = \frac{2}{\tau_B} - \frac{4}{t}. \quad \ldots\ldots\ldots\ldots(8)$$

$$m_3 = -\left[\frac{2R_O}{t} + \frac{R_O}{\tau_B} + \frac{1}{C_B}\right]. \quad \ldots\ldots\ldots\ldots \quad (9)$$

$$m_4 = \frac{4}{R_O t} - 2\,\frac{R_O + R_B}{\tau_B}. \quad \ldots\ldots\ldots\ldots\ldots \quad (10)$$

where $\tau_B = R_B C_B$ is the time constant of the transient response of the battery.

3.3. Formulation of the Objective Function for the Firefly Algorithm

The optimization problem of the developed battery model is to minimize the fitness (or objective) function formulated as

$$\min f_B = \left[1 - \frac{V_t}{\tilde{V}_t}\right] + \left[\frac{m_1(V_{t,k} - V_O) + m_2(V_{t,k-1} - V_O)}{m_3 I_{B,k} + m_4 I_{B,k-1}} + 1\right] + \beta. \quad \ldots\ldots\ldots\ldots \quad (11)$$

The first term of Equation (11) is to make sure that the optimized battery parameters give an accurate V_t while the second term models the internal dynamics (or behaviour) of the battery. The third term is a bias β introduced to prevent negative value of the estimated parameters, and it is formulated as:

$$\beta = \gamma \sum_{i=1}^{5} \left[\left(\frac{1}{p_{i,max} - p_i} + \frac{1}{p_i - p_{i,min}}\right)\left(\frac{p_{i,max} - p_{i,min}}{4}\right)\right]. \quad \ldots\ldots\ldots\ldots \quad (12)$$

where γ is a weighting factor of the bias and $p_i \in [R_o, R_B, \tau_B, V_B, V_o]$. The $p_{i,max}$ and $p_{i,min}$ for each i^{th} parameter are contained in Table 1. The values V_{o_min} and V_{o_max} were obtained as follows:

When the battery is charging (i.e. $I_B < 0$)

$$\begin{cases} V_{o_{min}} = V_t + I_B \times \left(R_{o_{max}} + R_{B_{max}}\right) \\ V_{o_{max}} = V_t + I_B \times \left(R_{o_{min}} + R_{B_{min}}\right) \end{cases} \quad \ldots\ldots\ldots\ldots\ldots \quad (13)$$

When the battery is discharging (i.e. $I_B > 0$)

$$\begin{cases} V_{o_{min}} = V_t + I_B \times \left(R_{o_{min}} + R_{B_{min}}\right) \\ V_{o_{max}} = V_t + I_B \times \left(R_{o_{max}} + R_{B_{max}}\right) \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots(14)$$

Table 1 Range of Values of the Battery's Parameters

Parameter	$\boldsymbol{p_{i,min}}$	$\boldsymbol{p_{i,max}}$
V_o	V_{o_min}	V_{o_max}
V_B	0.001 V	0.1 V
R_B	0.001 Ω	0.05 Ω
τ_B	1 secs	10 secs
R_o	0.001 Ω	0.1 Ω

The FA for the developed battery model is presented in Algorithm 1. The first step is the initialization of the FA parameters, battery parameters and the initial FA population. The population is a set of solutions (that is battery parameters to optimize). Each solution is a set of values of the battery parameters $[R_o, R_B, \tau_B, V_B, V_o]$. The next step is to rank each solution by evaluating the objective function using Equations (6) to (12). The solution with the minimum f_B is set as the brightest firefly (best solution). The best firefly is used to update all the other fireflies. The process is repeated until the maximum generation (iteration) is reached. The simulation specifications are contained in Table 2.

Algorithm 1 Firefly Algorithm (FA) for the Li-ion Battery Modelling

Inputs: Measured V_t, I_B (from flowchart of Figure 3.2) and FA parameters
Output: Optimized battery model parameters $[R_o, R_B, \tau_B, V_B, V_o]$
BEGIN
Maxite = 20; // maximum generation
Set $g = 0$; // first generation index
Generate N population (fireflies) by randomly assigning values to parameters
$p_{ij}[g] = [R_o, R_B, \tau_B, V_B, V_o]$; // $j = [1,2, \ldots, N]$
Compute the fitness value f_{B_j} of each firefly using Equations (3.6) to (3.12)
$F_{brightest}(p_{ij}[g]) = min(f_B)$ // best initial firefly
While g <= maxite **Do**
Compute the fitness value of each firefly using Equations (3.6) to (3.12)
Rank the fireflies according to their light intensity (minimum of f_B)
Set $F_{brightest} = min(f_B)$ // brightest firefly = brightest intensity
Move all fireflies towards the $F_{brightest}$
Update the population (new fireflies' generation)
$g = g + 1$; // next generation
End While
Optimized battery model parameters = $F_{brightest}$
END

Table 2 Lithium-Ion Battery Model Simulation Specifications

	Parameters	Values
	Battery Model	Panasonic UF553443ZU
	Nominal Voltage (V)	3.6
Battery	Rated capacity (Ah)	1
	Initial SoC (%)	100
	Maximum Discharge Voltage or Cut-off (V)	2.5
	Maximum Charge Voltage (V)	4.2
	Number population for Firefly	50
	Number of generations (or iterations)	20
Firefly Algorithm	Firefly randomness factor	0.5
	Randomness reduction	0.8
	Absorption coefficient	1.0

3.4. Performance Metrics

The performance of the developed battery model was evaluated using RMSE and MAE for obtaining the estimating error of the models in estimating the battery's behaviour.

3.4.1. Root Mean Square Error (RMSE)

The RMSE is used to evaluate the difference between the estimated values and the actual values; and the most effective metric for regression evaluation [2]. The RMSE is given as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \quad \text{..............} \quad (15)$$

where x_i is the actual (or true) value at the time step i; $\hat{x}_i$ was the predicted (or forecast) value at the time step i;

N was the number of steps in time.

3.4.2. Mean Absolute Error (MAE)

The MAE is a measure of the average of the absolute errors between the estimated values and the actual values; and the formular was:

$$MAE = \frac{\sum_{i=1}^{N}|x_i - \hat{x}_i|}{N} \quad \text{............}(16)$$

4. Results and Discussion

The voltage response to the injected charge and discharge current to the battery is presented in Figure 3. The voltage response is the measured terminal voltage V_t of the battery. The measurements were taken for 3600 seconds (or 1 hour). The results revealed that for every injected charge and discharge current pulse, a corresponding voltage value was obtained. Furthermore, the V_t value reduces as time increases. It was observed that the V_t reduced from the initial 4.20 V at the start of the discharge to about 3.57 V after the duration of the charge and discharge process.

In Figure 4, it is shown that the fitness converged at the 5th iteration (or generation) with a value 0.2242. Figure 5 shows that performance of the developed FA model for estimating the terminal voltage of the Li-ion battery. The estimated V_t values of the FA model were compared with the measured (or actual) V_t values for 1 hour duration. The result showed that the proposed model closely estimated the measured values with an RMSE value of 0.0443 and MAE value of 0.0052. The average estimation error incurred by the FA model was 8.2 mV.

The performance comparison between the developed FA model and the traditional Ah Counting method is presented in Figure 6. The evaluation is based on the OCV (Vo) versus SoC. The Reference on the graphs denotes results from [2].

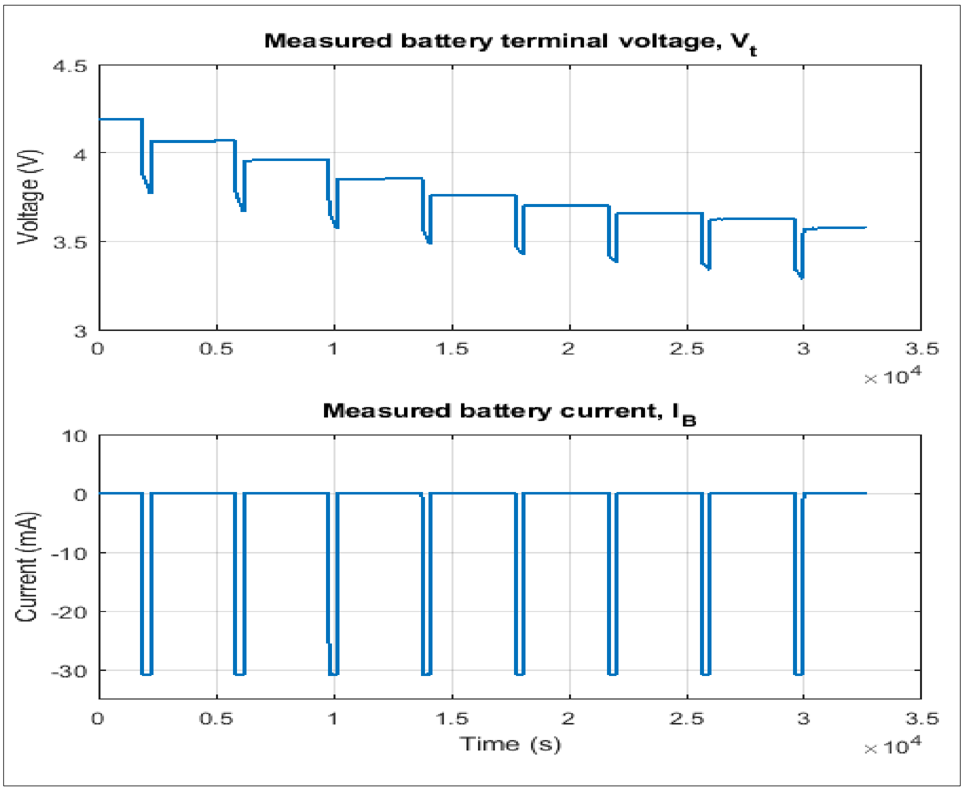

Figure 3 Charge and Discharge Profile of the Li-ion Battery

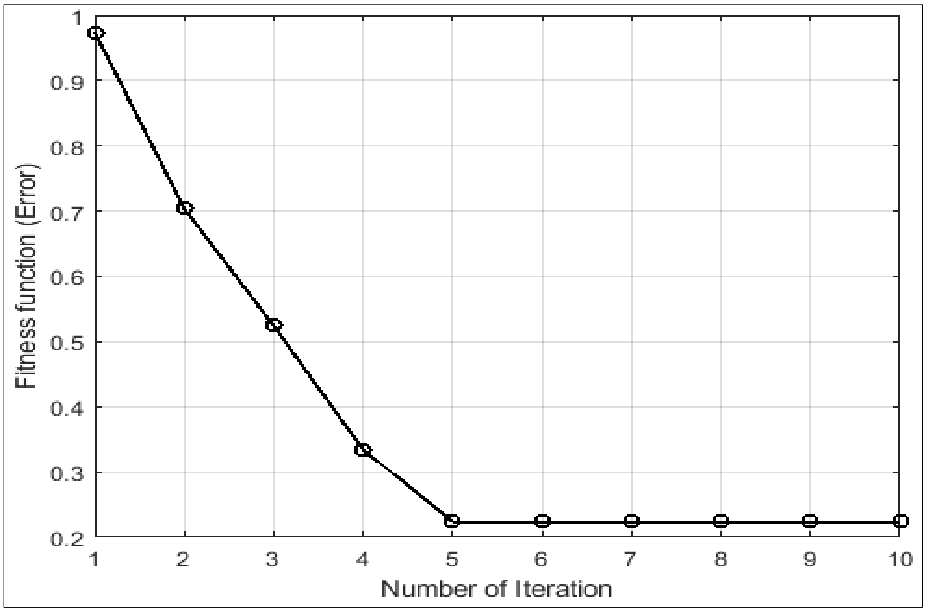

Figure 4 Best Fitness Values of the Firefly Population versus Iterations

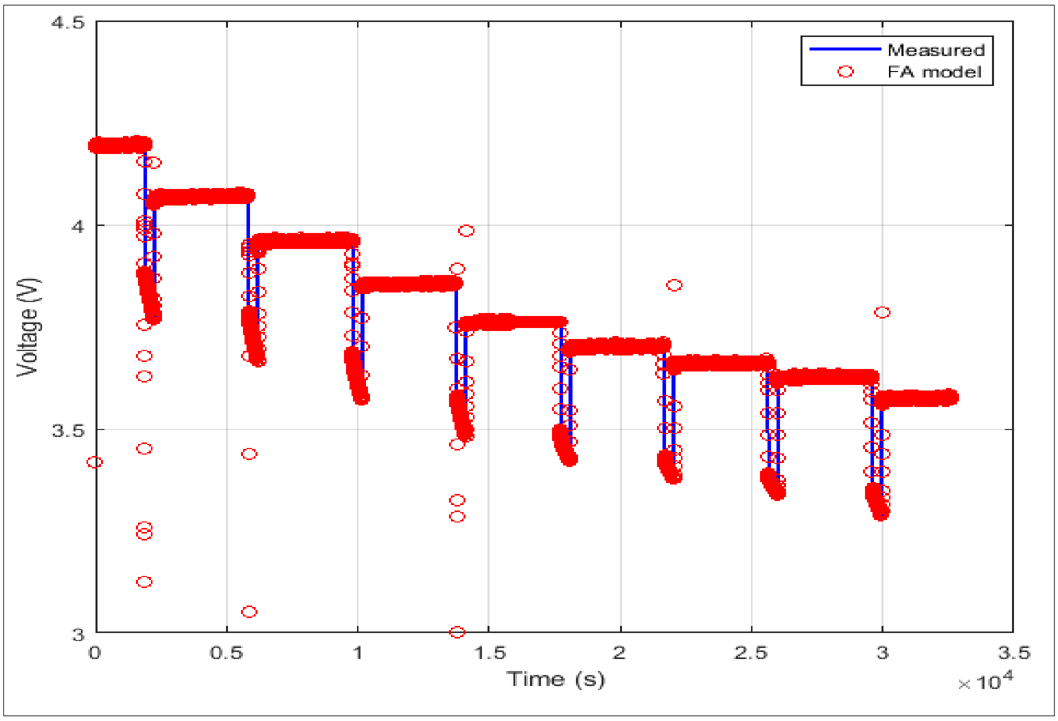

Figure 5 Battery's $\boldsymbol{V_t}$ Estimation Performance by the Developed FA Model

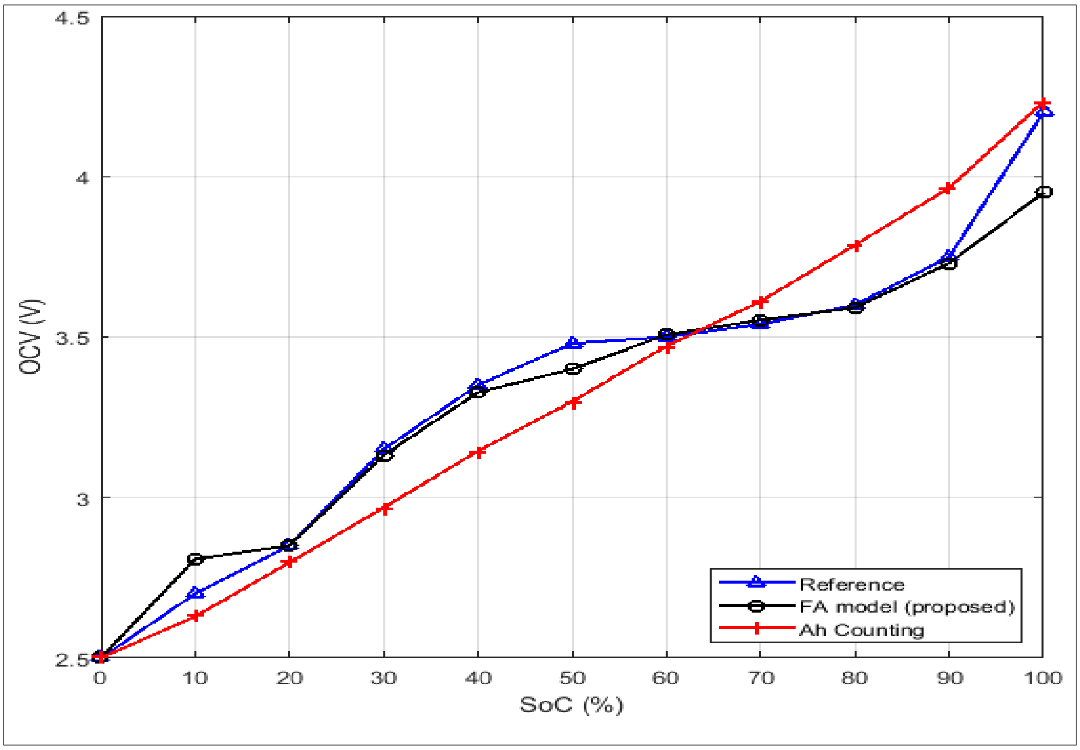

Figure 6 Battery's OCV versus SOC

It is observed that the OCV calculated by the FA model is in close agreement with the Reference OCV. The FA model gave MAE of 0.0479 whereas Ah Counting gave 0.1115. The RMSE results showed that the FA model and Ah Counting gave 0.0864 and 0.1361, respectively. These reveal that the FA model outperforms the Ah Counting in OCV-SoC estimation by about 57%. In addition, the FA model reveals the non-linear behaviour of the Li-ion battery whereas the Ah Counting is unable to reveal this behaviour.

The optimized battery parameter values at a time instant are contained in Table 3. It was observed that the developed model provided the parameters' values within their respective range.

Table 3 The FA Optimized Parameters of the Developed Li-ion Battery Model

Parameter	Optimized value
V_o (V)	3.5835
V_B (V)	0.0965
R_B (Ω)	0.0401
τ_B (secs)	6.6793
R_o (Ω)	0.0910
m_1	0.1503
m_2	0.2983
m_3	-0.0197
m_4	1.5833e+03

5. Conclusion

In this paper, a Lithium-ion (Li-ion) battery model for estimating the battery's terminal voltage, the OCV and SoC using the firefly algorithm (FA) was developed. The parameters of the Li-ion battery were modelled and optimized by the FA for estimating the battery's behaviour. The performance of the proposed model was evaluated using the RMSE and MAE. The results obtained showed that the FA model gives improved performance of about 57% in OCV-SoC estimation compared to the Ah Counting. In addition, the FA model gave an accurate terminal voltage estimation with less than 10 mV estimation error. This study has shown that the developed FA model for the Li-ion battery can estimate the behaviour of the battery for wireless sensors; thereby enabling improved monitoring and operation of a WSN.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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