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Parameter Identification and State-of-Charge Estimation for Lithium-Polymer Battery Cells Using Enhanced Sunflower Optimization Algorithm

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Abstract

This paper is concerned with the investigation of accurate parameter identification method and state of charge (SoC) estimation for Lion Lithium battery. The proposed identification method is implemented using an accurate state space model obtained from electric equivalent circuit. The process of parameter identification is expressed as nonlinear optimization problem. An Enhanced sunflower optimization algorithm (ESFOA) is employed to solve such problem. The search space is managed by applying the reduction strategy. This strategy is accomplished with the sunflower optimization algorithm to enhance the solution quality. **Three cases studied are considered as single and multi-objective frameworks. In these cases, battery voltage or SoC or combined between them as objective functions are optimized for the three cases studied.** Numerical simulations as well as experimental implementation are executed on 40 Ah Kokam Li-Ion Battery to prove the capability of the proposed parameter identification method. The ability of the proposed ESFOA is accomplished with high accuracy is proven compared with Water-Cycle and Whale optimization algorithms for two driving cycle profiles. Added to that, high closeness is achieved compared with the exper-

imental measurements for battery parameters and SoC. The solution quality improvement of the proposed ESFOA is noticed as it achieves the lowest the fitness function levels (in the range 60-90%) of the cases studied compared with the competitive optimization algorithms.

Keywords: Electrical model, Experimental analysis, Lithium-Polymer battery cells, Sunflower optimization algorithm, Parameter identification, State of charge estimation, optimization algorithms, driving cycle, reduction strategy.

1. Introduction

1.1. Motivation

The technology of Lithium-polymer cells is very attractive in the domain of energy-storage devices [1], [2]. This technology combines the following merits: very high energy and power densities allowing to use for plug-in hybrid electric vehicles (PHEVs). One of the major development of this technology is the lithium-ion (Li-ion) battery [3], [4]. The battery management systems have a crucial role for the power efficiency of transportation systems. Their role ensures the optimal energy consumption and to make energy management system information to be available for the vehicular in normal and abnormal operating conditions [5]. The SoC estimation is an urgent prerequisite to achieve a good supervising and controlling of battery charging and discharging [6]. Moreover, accurate estimation of battery parameters and SoC represents an urgent need for many reasons such as extending battery life, battery state of charge controlling, improving the battery performances [7], optimizing the energy management, supervising the safety of the battery [8], [9], [10].

1.2. Literature Review

The battery is a complex non-linear and non-stationary electrochemical system. This non-linearity of the battery is due to the fact that the relationship between the current applied at the input and the voltage recovered at the output cannot be expressed by a linear

relationship. The battery is non-stationary because the characteristics of the internal electrical parameters of the battery are variable during a charge/discharge cycle and during its life cycle [11]. The definition of the parameters value and equation type of a battery model is based on the exploitation of the battery voltage curves (output) as a function of a current profile input). However, the power or current profiles directly derived from measurements or estimated in relation to normalized driving cycles in electric vehicle applications are relatively complex. There are several approaches in the literature to simplify these profiles, based on statistical counting and classification methods.

Different battery models have been investigated in the literature according to the target accuracy degree and the practical application such as electric vehicles. An efficient dynamic model that comprising two elements, resistance and capacitor (RC) in its equivalent circuit was proposed [12]. Several works have been proposed in the literature to address the parameters identification and SoC estimation. These methods can be classified as follows:

- Ampere-hour counting method which has economical and technical benefits, low current sensors costs and low power consumption [13].
- Open-circuit voltage (OCV) estimation method, the OCV and SoC relationship is exploited for all battery technologies SoC estimation [14]. This relationship changes slightly over battery lifetime, which represents one of the most advantages of this method.
- Impedance-based estimation method, the battery SoC is dependent on some of its impedance parameters which boost researchers to identify this parameters for the SoC estimation [15]. The dependence of the SoC on the impedance parameters changes significantly over the battery lifetime which represents the main drawbacks of this method [16].
- Static battery characteristics estimation method, it consists to use the battery voltage,

current and temperature relationship when the battery load rests constant to estimate the SoC [17].

- Artificial intelligence estimation methods [18], the artificial intelligence methods have been applied for SoC estimation, such as fuzzy logic (FL), neural network (NN) [19], ANFIS, support vector machines (SVMs).
- Measurement techniques based estimation, several approaches have been proposed in this category one of them uses additional sensors are used for the battery magnetic characteristic measurement which can be considered as an indicator for the SoC [20].
- Model-based estimation method, Its principle is the use of the battery measurements such as the voltage, the current and the temperature to design such battery model. The relationship of the battery SoC and OCV is used to incorporate the SoC into the battery model. In this model the SoC is represented by a state equation. This model can be used therefore to estimate the SoC using the measurements as inputs. Two model types are generally employed, the electrical one is the famous model type for SoC estimation [6].

Among the previous estimation methods, the electrical battery model is widely used to identify the battery parameters and to estimate the SoC. Based on this model, several parameter estimation methods were developed such as observers in [21], classical identification methods [22], on-line estimation procedure was presented in [23].

The state observer based methods have been largely used in the literature allowing to an online identification of battery parameters. The used methods are sliding-mode observer, Luenberger observer [24], Kalman filter, adaptive observers [25]. For these methods, the observability of battery models is rarely studied. Moreover it is not always easy to prove the stability of the proposed observer. Machine learning and artificial intelligence techniques such as neural network [26] have been used to estimate the SoC and the battery parameters,

support vector machine [27] and multi-variable adaptive regression splines [28].

In recent decades, continuous development is noticed in the application of recent evolutionary optimization techniques in variant engineering and science fields. These algorithms have been adopted to solve various engineering optimization problems such as neural network algorithm [29] and particle swarm optimization (PSO) [30], have been employed in optimization and applied inverse methods due to their excellent global search abilities. The estimation algorithms and on-line parameter identification methods are needed to guarantee the accuracy of the model-based SOC estimation with nonlinear battery models. On the other hand, numerous the parameters and SoC estimation based on optimization algorithms such as particle swarm optimization [30], Hybrid Particle swarm-Nelder-Mead algorithm [31] and some other classical optimization algorithms have been proposed to estimate the machine parameters based generally on algebraic models. In [32] grey wolf optimization algorithm has been compared with PSO and genetic algorithm techniques for only parameters estimation of lithium battery based on algebraic model.

Several efforts with the application of recent optimization algorithms were developed for solving energy applications such as parameter estimation of solar cells such as [33], technical, economical and environmental scheduling of energy resources [34], [35], electrical based integration of renewable energy into stand-alone systems [36], and for energy management of hybrid renewable energy resource as presented in [37] and [38]

In 2018, the SFOA is one of the meta-heuristic algorithms that was firstly proposed by Gomes and others [39] in their work about identification of damage on laminated composite plates. Another application of SFOA for parameter estimation of three diode models of solar cell in [40]. SFOA stimulated by the sunflowers movement towards the sunlight [39]. The SFOA is stimulated by the inverse-square law of radiation intensity, where the amount of heat is proportional to the squared distance between sunflowers and the sun.

1.3. Paper contribution

In this paper, an enhanced version of sunflower optimization algorithm is investigated for parameter identification and SoC estimation. The salient features of the proposed method can be summarized as follows:

1. Using the non-linear electrical circuit for modeling lithium battery with state space representation .
2. Developing the ESFOA based on reduction strategy to enhance the search space in order to obtain the optimal parameters and to estimate SoC of lithium ion battery.
3. Three cases are considered to simulate single and multi-objective frameworks. The objectives measure the closeness between the estimated and experimental recorded for the terminal battery voltage and state of charge.
4. A comparison study is employed to show the capability of the proposed ESFOA.
5. Assessing the sunflower optimization algorithm with water-cycle and whale optimization algorithms.

1.4. Paper structure

The following sections of the current work are organized as follows: Section 2 presents to the state space dynamic modeling of the lithium ion battery. The estimation problems of battery parameters and state of charge are formulated as optimization problem with single and multiobjective frameworks in Section 3. Section 4 presents the sunflower optimization algorithm for solving the predefined problem in section 3. Section 5 presents the setup of experimental works and the related bench marking driving cycle. Section 6 concludes the current research findings.

2. Lithium Ion Battery modeling

The common used equivalent circuit model is constructed with n times RC elements denoted by n RC model [41], normally up to 3 RC elements are used [42]. In this paper, a

reduced model with $n=1$ i.e single RC model is considered as shown in Fig. 1. The battery model is modeled by using RC equivalent circuit as shown in Fig. 1. The relaxation effect is represented by RC group. This model avoids the complexity raised for the problem of parameters identification. The following subsections describe the mathematical and state space model of the battery. Equation (1) presents a linear relationship to describe the static characteristic of the battery under predetermined conditions of temperature and age, between the V_{oc} and SoC is assumed as [43] as:

$$V_{OC} = f(SOC) = b_0 + b_1 SOC. \quad (1)$$

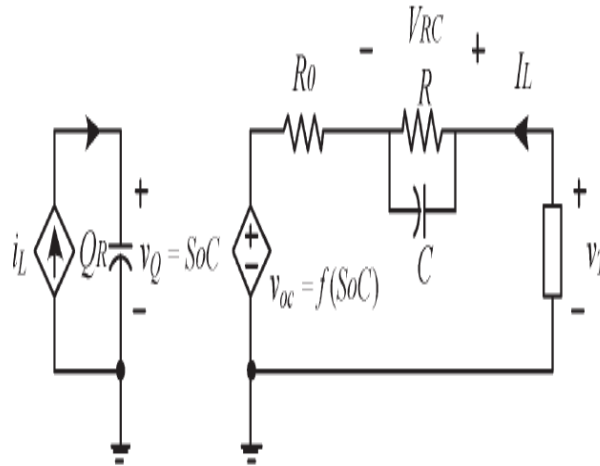


Figure 1: Battery equivalent circuit.

The parameters identification and SoC estimation problem is formulated as state space model. Based on Fig. 1 and Eq. (1), the state space model for the battery dynamics is represented in the following form:

$$\dot{X} = AX + Bu \quad (2)$$

$$y = CX + Du + b_0 \quad (3)$$

where,

$$X = \begin{bmatrix} SOC \\ V_{rc} \end{bmatrix},$$

$$A = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{RC} \end{bmatrix}, B = \begin{bmatrix} \frac{1}{Q_R} \\ \frac{1}{C} \end{bmatrix}, C = \begin{bmatrix} b_1 & 1 \end{bmatrix}, D = R_0.$$

V_T and I_L are the battery terminal voltage and current, respectively. R_0 is the internal resistance. Q_r is assumed to be the nominal battery capacity. In the current work, the terminal voltage (V_T) and current (I_L) values are assumed to be accessible from the state space dynamic model in Fig.1. Both the temperature and ageing of the battery effects are not considered in this work.

According to the system Eqs. (2) and (3), the battery parameters are identified for state of charge estimation as well as computing the terminal battery voltage.

3. Problem formulation

3.1. Parameterization model development

The dynamic model of the battery described in the previous section is used **to identify the battery parameters to estimate state of charge**. To optimize the parameters of the Li-ion battery model, an objective function has to be set for fitting the estimated output voltages **with the corresponding recorded voltage in the experimental tests**. The proposed objective function is based on the minimization of Squares Error Sum (SSE) between the experimental data and the model-based simulation results. The general representation of the proposed optimization problem takes the following form:

$$\min_u F_i(u), i = 1, 2..nobf \tag{4}$$

$$u_{min} \leq u \leq u_{max}$$

where, $F_i(u)$ is the objective function i , u is the estimated parameters of the battery, N is the number of the estimated and u_{min} , u_{max} are the parameter bounds of control variable's vector u that are reflected the accepted research domain, $nobj$ is the number of objective functions.

The identification of the model parameters is based on the exploitation of the battery experimental data.

3.2. Objective functions

In the proposed method, three cases studied are considered. these cases can be defined as follows:

1. Minimizing the normalized deviation between the estimated and experimental battery voltage $F_1(u)$ with Equation (5) which is considered as the primary objective function of the considered problem as

$$F_1(u) = \sum \left(\frac{\hat{V}_{bat} - V_{ex}}{V_{bat}^{max}} \right)^2; \quad (5)$$

where \hat{V}_{bat} is the value of the estimated battery model voltage. However, V_{bat} is the recorded experimental battery voltage.

2. Minimizing the normalized deviation between the estimated and experimental state $F_2(u)$ of charge with aid of Equation (6). this equation is considered as the primary objective function instead of 5 in the previous case as

$$F_2(u) = \sum \left(\frac{\hat{SOC} - soc}{soc^{max}} \right)^2; \quad (6)$$

where \hat{SOC} is the value of the estimated battery state of charge.

3. Providing a multi-objective function MoF for parameter estimation of the battery by combining Equations (5) and (6). This objective function aims to minimize simultane-

ously the deviation between the estimated and experimental battery voltage and state of charge. The common multi-objective function of the battery model identification is given by:

$$MoF(u) = w_1 \times \sum_{i=1}^n \left(\frac{V_{\hat{bat}} - V_{ex}}{V_{bat}^{max}} \right)^2 + w_2 \times \sum_{i=1}^n \left| \left(\frac{S\hat{OC} - soc}{soc^{max}} \right)^2 \right| \quad (7)$$

where, w_1 and w_2 represent the weighting factors that reflect the degree importance of F_1 and F_2 .

3.3. Constraints

The previous objective functions, Eqs. (5)–(7), are solved by using ESFOA subject to the following constraints:

$$R_{min} \leq R \leq R_{min} \quad (8)$$

$$R_{0min} \leq R_0 \leq R_{0min} \quad (9)$$

$$C_{min} \leq C \leq C_{min} \quad (10)$$

$$b_{0min} \leq b_0 \leq b_{0min} \quad (11)$$

$$b_{1min} \leq b_1 \leq b_{1min} \quad (12)$$

$$Q_{rmin} \leq Q_r \leq Q_{rmin} \quad (13)$$

where *min* and *max* operators refer the minimum and the maximum values of the identified parameters.

4. Sunflower solution methodology

4.1. ESFOA concept and mathematical representation

The concept of sunflower optimization algorithm (ESFOA) simulates the motion of the sun flowers toward the sunlight. It is dependent on pollination intensity between the close-ness sunflowers. ESFOA is considered as a new optimization algorithm that is dependent on the inverse square law radiation [39], [40], [44] as:

$$S_r = \frac{S_p}{4\pi d^2} \quad (14)$$

where S_r is the solar radiation intensity, S_p is defined as the sun power, d is the distance between the sun and the sunflower. Sunflower (s_i) is moved toward the sun, and its direction is determined by equation

$$\vec{S}_i = \frac{X^* - X_i}{\|X^* - X_i\|}, \quad i = 1, 2, \dots, n_p. \quad (15)$$

where X_i is the current position of sunflower i , X^* is the best solution among n_p sunflowers. The norm operator is denoted by $\|\cdot\|$. The updating equation for sunflower direction toward to the sun is represented by:

$$\bar{X}_{i+1} = \bar{X}_i + d_i * \bar{S}_i \quad (16)$$

where X_{i+1} is the updated position of sunflowers.

$$d_i = \lambda * P_i(\|X_i + X_{i-1}\|) * \|X_i + X_{i-1}\| \quad (17)$$

where d_i is the step of sunflower toward the direction of the sun. Where λ is the sunflower inertial displacement. $P_i(\|X_i + X_{i-1}\|)$ refers to the probability of two adjacent sunflowers

(i and $i - 1$) pollination. The step transition is limited by Eq. (18) as:

$$d_{max} = \frac{X_{max} - X_{min}}{2 * N_{pop}} \quad (18)$$

where X_{min} and X_{max} are the boundaries values, N_{pop} is the population size of sunflowers.

Applying the reduction strategy aims to concentrate the search space and therefor enhance the overall solution quality. In this strategy, the search space is managed through adaptive variation of the upper and lower limits according to (19) and (20).

$$X_{min} = X_{min} + \alpha * (X_{max} - X_{min}) \quad (19)$$

$$X_{max} = X_{max} - \alpha * (X_{max} - X_{min}) \quad (20)$$

The factor α refers to the reduction coefficient that is applied in reduction strategy to manage the minimum and maximum bounds.

4.2. Proposed ESFOA-based solution methodology

The procedure of sunflower solution methodology can be mentioned as:

1. Define the ESFOA parameters and building the state space model Eqs. (2) and (3).
2. Initialization process of the random position of n_b flowers. Each sunflower represents the decision variables *i.e* the target estimated parameters within their boundaries.
3. Evaluation process of the initial positions to catch the best solution S^* using Eqs. (5) and (6) for single objective cases and Eq. (7) for multi-objective case.
4. Employ the orientation of N_{pop} sunflowers to the sun direction.
5. while ($k < \text{Maxiteration}$)
 - (a) Reduce the population size by m (%)
 - (b) Compute each plant step using state space model (2)-(3)

- (c) Re-evaluate the new position using Eqs. (5), (6) and (7)
 - (d) For the global best individual update the sunflower second level
6. Apply the reduction strategy to enhance the search space and enhance the solution quality. The strategy is integrated using Eqs. (19) and (20). In this paper the factor α equals 0.08.
 7. For each plant compute the vector of the orientation
 8. Check the stopping criteria
 9. Print the identified variables

5. DESIGN OF EXPERIMENT

In this context, we have laboratory experimental tests based on constraints classification in intensity levels. Its objective is to reduce cycling times while maintaining the most important characteristic variables for test profiles, such as the maximum current intensity and the amount of charge exchanged. The simplification adopted in this approach allows us to move from a complex pulse current profile to a signal in the form of a current step with well-defined current values. For more details about the simplification of the real current profile, using the heuristic method based on constraints classification, please refer to [45], [46]. Before applying this constraints classification, the common ARTEMIS driving cycle is chosen for identifying the parameters of the battery model by using a dynamics model of the urban electric vehicle (BollorÃ© Bluecar).

5.1. Driving cycle

In the last few years, several normalized and non-normalized driving cycles have been recently proposed with the aim of evaluating pollution emissions and fuel consumption of gasoline-powered engines. One can cite for examples the UDC, ECE, NEDC, ARTEMIS, FTP75, NYCC and WLTC [47].

The representation of any driving cycle is generally based on speed-time sequences that represent the traffic conditions and driving behavior in a specific area. For this study, the ARTEMIS driving cycle (Assessment and Reliability of Transport Emission Models Inventory Systems) is selected. The latter is considered as a part of the main European project which induced in the creation of a transient driving cycle based on other European driving cycles [8]. It is divided into three phases (urban, rural and highway), which are representative of real-world driving behavior. In this study, the ARTEMIS cycle chosen is represented by the urban and the rural cycle. Therefore, the distance covered is about 22km in 2075 seconds for an average speed of 38.4km/h and a maximal speed of 111.5 km/h.

5.2. Laboratory test bench and battery technology

A test bench is used to carry out accelerated cycling aging tests while trying to be as close as possible to the electric vehicle application. The laboratory test bench is as shown in Fig. 2, the bench includes two main components: a climatic chamber and charge/discharge setup. The power that can be delivered by this bench in continuous operation is 10kW, by using a programmable power supply. The latter is connected to a reversible four-leg power converter (60V/ 600A). The FPGA compact RIO NIcRIO-9012/9014 real-time control system with LabVIEW software is used for setting up the test procedure and for data acquisition [31] [46]. Battery cells are placed in the climatic chamber in order to perform the test at controlled temperature conditions. These units can change the temperature from 0 to 100 $\hat{\text{A}}^{\circ}\text{C}$ and are able to change the temperatures at a rate of $3 \pm 0.02\hat{\text{A}}^{\circ}\text{C}$. The man-machine interface (MMI) in Fig. 3 shows the front panel of RealTime (RT). It allows entering the parameters related to control and acquisition, as well as the management of the safety of the bench (maximum and minimum limits of the voltages and currents tolerated by the components, maximum temperature limit...etc). This interface also allows us to visualize information on the state of the bench (defects, type of defect, backup activation, number of cycles performed...etc) and to visualize the evolution of the electrical values and the temperatures of the components.

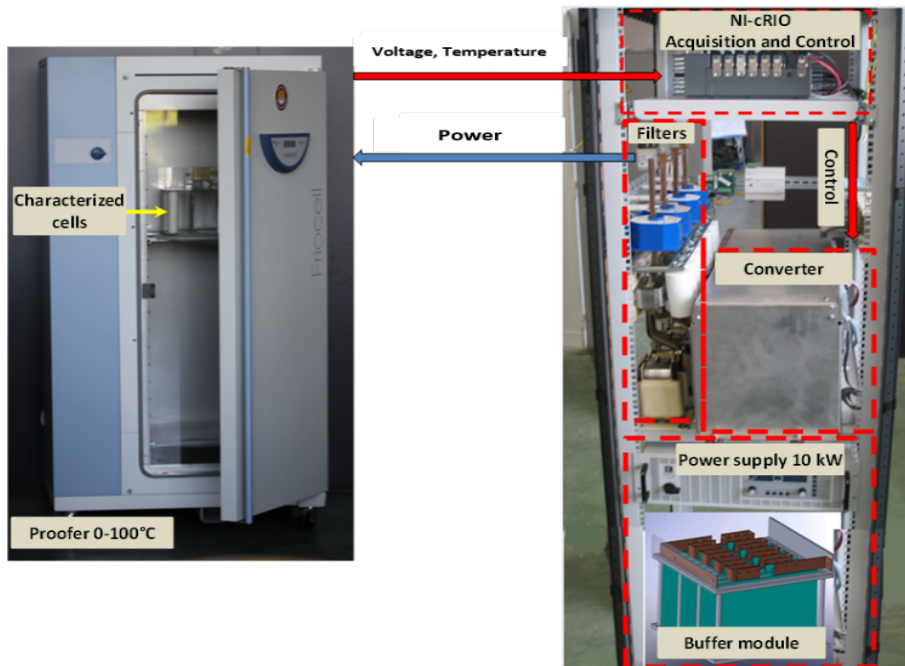


Figure 2: (a) Laboratory test bench. (b) MMI interface for control and monitoring of the test bench.

Different types of batteries have been recently designed for electric and hybrid vehicles with the aim of improving the tradeoff between drive performance and high reliability [48]. As an example, a commercial 40 Ah Li-ion battery cell produced by Kokam manufacturer,

under the references HED- SLPB90216216 is used in our study. Table 1 gives the specifications of Li-ion battery cells, which present their most relevant specifications that can be found in the datasheet.

Table 1: Characteristics Of Kokam Li-Ion Battery Technologies [31]

Battery	Kokam 40 HED
Nominal voltage (V)	3.7
Internal resistance (m)	0.9
Capacity (Ah)	40
Specific Energy (Wh/kg)	167
Max current cha/dis (A)	40/40
Weight (kg)	0.885

Figure 6 (first figure) illustrates the cycling current profile 150 km ARTEMIS driving cycle (setpoint current) superimposed on the real current profile by using the tested battery, Kokam Ko40HE. With the heuristic method based on constraints classification, the duration of cycles is reduced by 35% of the real profiles. As for the recharge phase, it occurs when the desired depth of discharge is obtained. This recharging reduces the state of charge of the batteries to 100%. The recharge follows the protocol defined by the manufacturer Kokam. This profile consists of a CC/CV (Constant Current/Constant Voltage) recharge, preceded by a rest phase. In this study, the used battery has been designed for a range of 150 km. The cycling profiles are obtained by using the constraints classification method and it was repeated seven times to correspond to the 150km distance and to obtain a depth of discharge of 80%.

5.3. Evaluation of the estimated results

In this section, the simulation results obtained by applying the proposed ESFOA are assessed with those recorded in the experimental results and two other optimization algorithms

called water-cycle (WCOA) and whale (WOA). The WCOA parameters are customized from [49] while the parameters of WOA are taken from [50].

Table 2 shows the parameters of the proposed ESFOA. Table 3 presented the boundaries of the estimated battery parameters according the experimental tests. The discharge with constant current and CC/CV charge protocol is used to record the experimental voltage data of battery. In addition, the change of SoC during the test has been recorded with a coulomb-accumulation method based on the history of current, including self-discharging and current inefficiency on charge. As mentioned above three cases are studied. In the first case, the primary objective function aims at minimizing the deviation between the estimated and recorded battery voltages. According to Table 4, Figs 3 and 6 shows the battery performance for two tested driving cycles. It is cleared that: the high closeness between the estimated and measured variables are achieved for both battery voltages and the battery state of charge. The primary objective function reaches 5.23×10^{-5} while the second objective reaches 6.58×10^{-6} .

By the transition to Case 2, the minimizing of SOC is considered as the primary objective function while the battery voltage is considered as secondary objective. In Case 2, high closeness is noticed between the estimated and measured state of charge for both tested driving cycles. The simulation results of the estimated SoC is presented in Table 5, Figs 4 and 7. The primary objective function reaches 7.8×10^{-5} while the secondary objective function (battery voltage) reaches 2.1×10^{-8} . A compromise solution is obtained between the considered two objective functions, battery voltage and state of charge, in Case 3. The two objective functions are simultaneously optimized for both tested driving cycles. The simulation results are presented in Table 6, Figs 5 and 8. The considered objective functions reaches 6.23×10^{-5} and 3.5×10^{-8} , respectively.

From Tables 4-6, it is concluded that the ESFOA leads to the lowest fitness functions (in the range 60-90%) and competitive parameter identification for the three cases compared

with the WCOA and WOA.

Table 2: Sunflower optimization algorithm parameters

Population size	Pollination rate	Mortality rate	survival rate	Maximum iteration
50	0.1	0.005	0.9	40

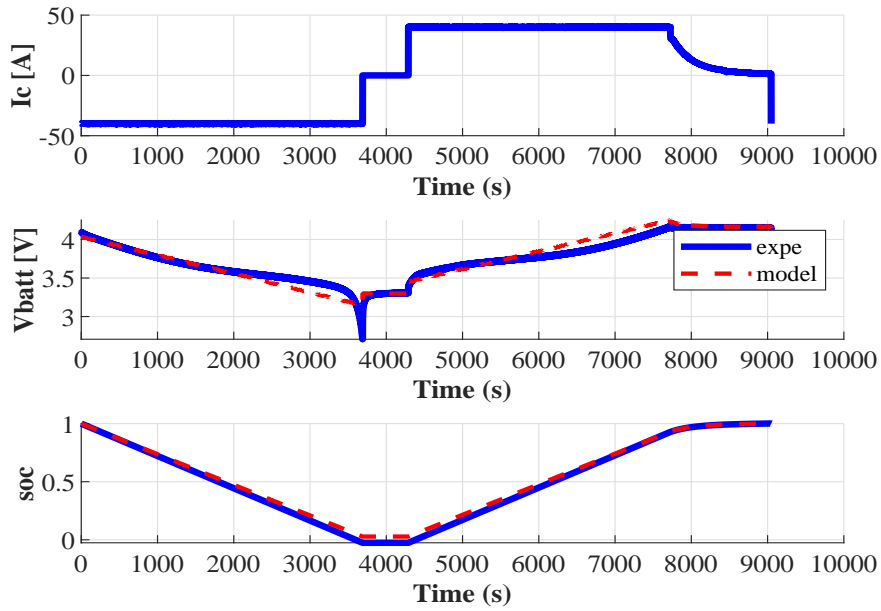


Figure 3: Case 1 (a) Constant current profile with CC/CV charge protocol. (b) Experimental and modeling responses of battery voltage . (c) Experimental and modeling responses of battery SoC .

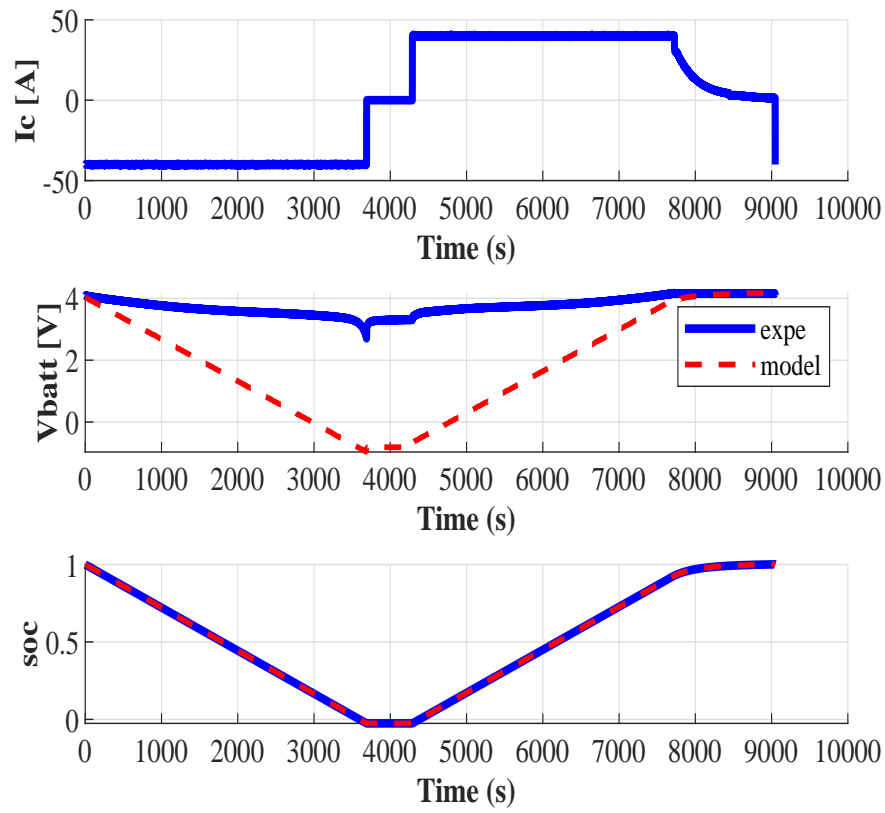


Figure 4: Case 2 : (a) Constant current profile with CC/CV charge protocol. (b) Experimental and modeling responses of battery SoC .

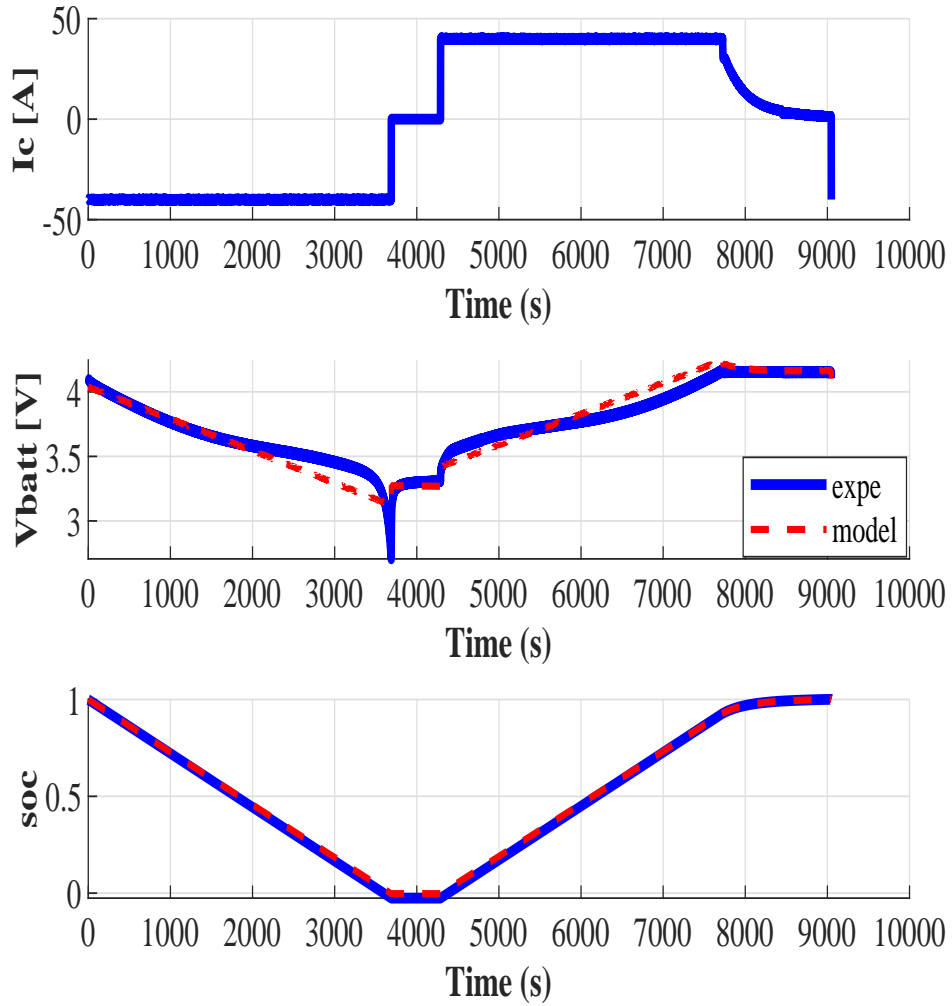


Figure 5: Case 3 (a) Constant current profile with CC/CV charge protocol.(b) Experimental and modeling responses of battery voltage . (c) Experimental and modeling responses of battery SoC .

Table 3: Identified battery parameters

	R ($m\Omega$)	Ci (F)	Ri (Ω)	b0 (V)	b1 (V)	Qr
LB	3	4000	1000	-3	25	130000
UB	4	5000	1300	-5	40	170000

Table 4: Identified battery parameters Case 1

	R	Ci	Ri	b0	b1	Qr	F1	F2	Fitness
WCOA	3.77	4396.46	1110.30	-4.24	34.40	147320.27	$5.23 \cdot 10^{-5}$	$6.58 \cdot 10^{-6}$	$5.23 \cdot 10^{-5}$
WOA	3.38	4306.56	1001.49	-3.72	31.75	135999.34	$3.3 \cdot 10^{-4}$	$2.6 \cdot 10^{-4}$	$3.3 \cdot 10^{-4}$
ESFOA	3.77	4396.46	1110.30	-4.24	34.40	147320.27	$5.23 \cdot 10^{-5}$	$6.58 \cdot 10^{-6}$	$5.23 \cdot 10^{-5}$

Table 5: Identified battery parameters Case 2

	R	Ci	Ri	b0	b1	Qr	F1	F2	Fitness
WCOA	3.65	4529.28	1101.74	-3.72	30.35	147963.81	$5.7 \cdot 10^{-4}$	$1.68 \cdot 10^{-7}$	$1.68 \cdot 10^{-7}$
WOA	3.81	4586.68	1183.69	-4.55	35.37	147963.81	$6.2 \cdot 10^{-4}$	$5.82 \cdot 10^{-7}$	$5.82 \cdot 10^{-7}$
ESFOA	3.77	4396.46	1110.30	-4.55	34.40	147320.27	$7.8 \cdot 10^{-5}$	$2.1 \cdot 10^{-8}$	$2.1 \cdot 10^{-8}$

Table 6: Identified battery parameters Case 3

	R	Ci	Ri	b0	b1	Qr	F1	F2	Fitness
WCOA	3.77	4396.46	1110.30	-4.24	34.40	147320.27	$6.23 \cdot 10^{-5}$	$7.12 \cdot 10^{-7}$	$6.24 \cdot 10^{-5}$
WOA	3.66	4515.54	1084.95	-3.72	32.38	145804.00	$3.5 \cdot 10^{-4}$	$7.39 \cdot 10^{-6}$	$3.6 \cdot 10^{-4}$
ESFOA	3.66	4634.52	1107.23	-4.13	32.71	1.4797 10	$6.23 \cdot 10^{-5}$	$3.5 \cdot 10^{-8}$	$6.23 \cdot 10^{-5}$

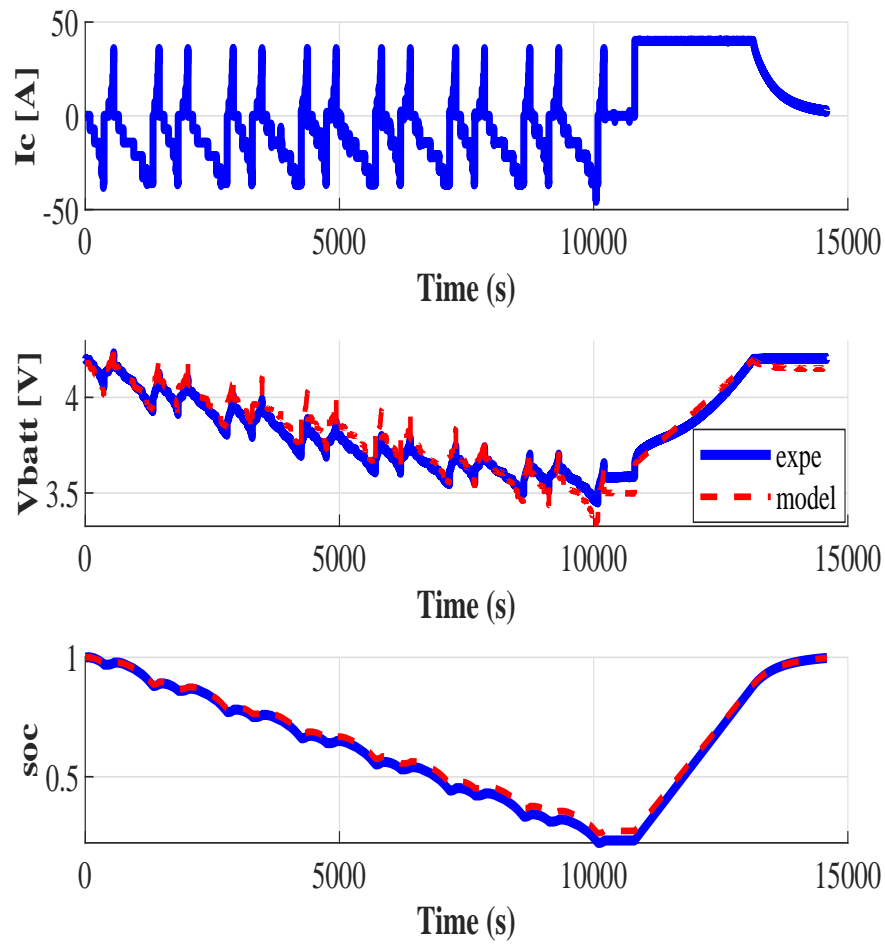


Figure 6: Case 1 (a) Laboratory current profile with 150 km ARTEMIS driving cycle. (b) Experimental and modeling responses of battery voltage . (c) Experimental and modeling responses of battery SoC .

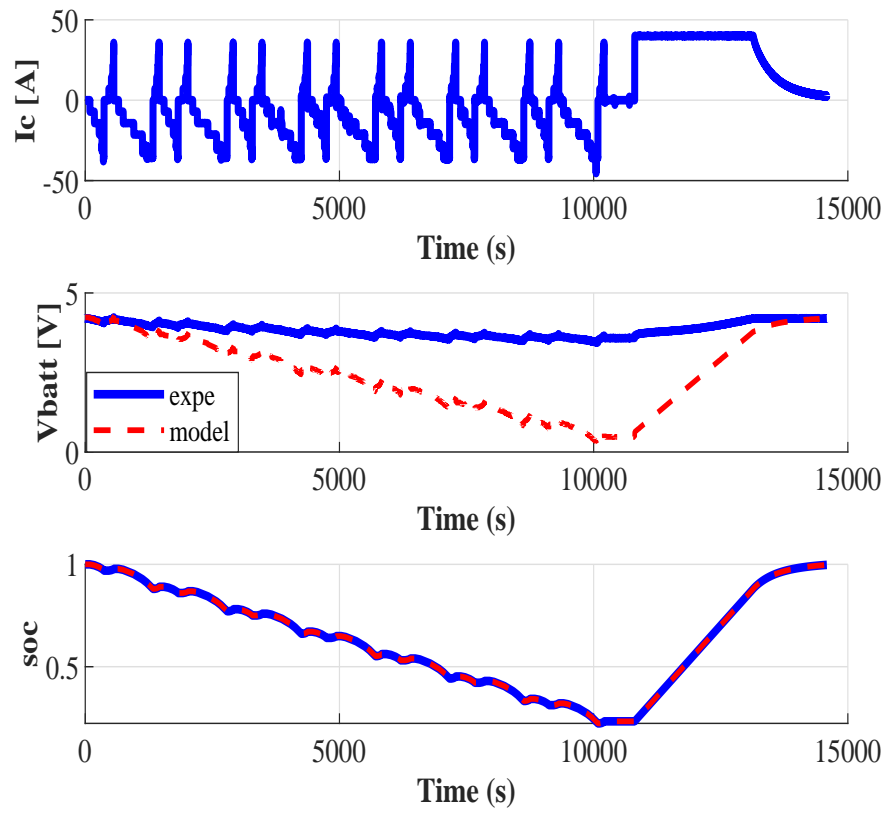


Figure 7: Case 2 : (a) Laboratory current profile with 150 km ARTEMIS driving cycle. . (b) Experimental and modeling responses of battery SoC .

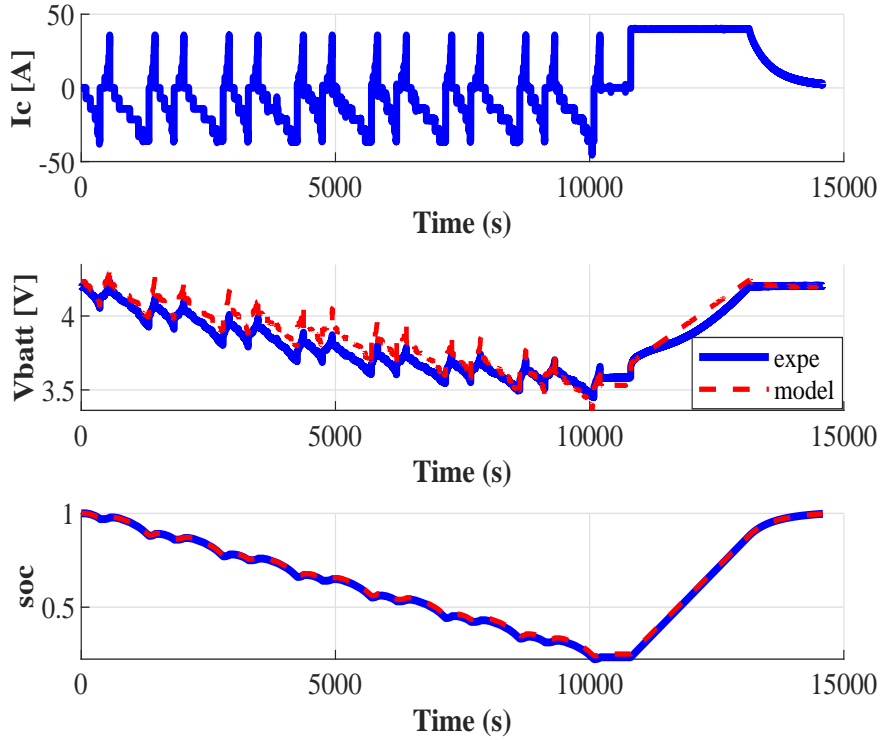


Figure 8: Case 3 (a) Laboratory current profile with 150 km ARTEMIS driving cycle. (b) Experimental and modeling responses of battery voltage . (c) Experimental and modeling responses of battery SoC .

6. Conclusion

This paper has been proposed a **n enhanced sunflower optimization algorithm for solving the problem of parameter identification and state of charge estimation of Lithium Polymer Battery Cells**. An electrical dynamic equivalent circuit based on state space model has been presented. The problem of parameter identification is formulated as non-linear optimization problem. Multi-objective sunflower optimization algorithm is developed to simultaneously optimize two objective functions and to obtain the optimal parameter identification and estimate the state of charge. Both objectives aim at achieve the high closeness between experimental and estimated values for voltage and state of charge of the considered battery.

This paper proves the ability of the proposed sunflower optimization algorithm as accurate method for obtaining the optimal battery parameters. The proposed parameter identification procedure has been validated for constant and varied current profiles, that is reflected real **bench-marking** driving cycles. The error levels among simulation results **reflect** high closeness between the estimated and experimental data.

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References

- [1] P. Wu, R. Bucknall, [Hybrid fuel cell and battery propulsion system modelling and multi-objective optimisation for a coastal ferry](#), International Journal of Hydrogen Energy (2019). doi:<https://doi.org/10.1016/j.ijhydene.2019.11.152>.
URL <http://www.sciencedirect.com/science/article/pii/S0360319919343757>
- [2] J. Lin, L. Yu, Q. Sun, F. Wang, Y. Cheng, S. Wang, X. Zhang, [Multiporous core-shell structured mno@n-doped carbon towards high-performance lithium-ion batteries](#), International Journal of Hydrogen Energy (2019). doi:<https://doi.org/10.1016/j.ijhydene.2019.11.083>.
URL <http://www.sciencedirect.com/science/article/pii/S036031991934265X>
- [3] R. Milocco, J. Thomas, B. Castro, Robust polynomial approach for state of charge estimation in nimh batteries, International Journal of Hydrogen Energy 37 (13) (2012) 10371 – 10375.
- [4] S. Boudoudouh, M. MaÃroufi, [Real-time battery state of charge estimation in smart grid application by multi agent system](#), International Journal of Hydrogen Energy 42 (30) (2017) 19487 – 19495. doi:<https://doi.org/10.1016/j.ijhydene.2017.06.077>.
URL <http://www.sciencedirect.com/science/article/pii/S0360319917323534>
- [5] D. F. Frost, D. A. Howey, Completely decentralized active balancing battery management system, IEEE Transactions on Power Electronics 33 (1) (2017) 729–738.

- [6] H. Ramadan, M. Becherif, F. Claude, Extended kalman filter for accurate state of charge estimation of lithium-based batteries: a comparative analysis, *International Journal of Hydrogen Energy* 42 (48) (2017) 29033 – 29046.
- [7] M. Yue, S. Jemei, R. Gouriveau, N. Zerhouni, [Review on health-conscious energy management strategies for fuel cell hybrid electric vehicles: Degradation models and strategies](#), *International Journal of Hydrogen Energy* 44 (13) (2019) 6844 – 6861. doi:<https://doi.org/10.1016/j.ijhydene.2019.01.190>. URL <http://www.sciencedirect.com/science/article/pii/S0360319919303490>
- [8] Q. Liao, M. Mu, S. Zhao, L. Zhang, T. Jiang, J. Ye, X. Shen, G. Zhou, Performance assessment and classification of retired lithium ion battery from electric vehicles for energy storage, *International Journal of Hydrogen Energy* 42 (30) (2017) 18817 – 18823.
- [9] L. Zhan, X. Zhou, J. Luo, X. Ning, [Ion assisted anchoring sn nanoparticles on nitrogen-doped graphene as an anode for lithium ion batteries](#), *International Journal of Hydrogen Energy* 44 (45) (2019) 24913 – 24921. doi:<https://doi.org/10.1016/j.ijhydene.2019.07.153>. URL <http://www.sciencedirect.com/science/article/pii/S0360319919327296>
- [10] B. Bendjedia, N. Rizoug, M. Boukhniifer, F. Bouchafaa, M. Benbouzid, [Influence of secondary source technologies and energy management strategies on energy storage system sizing for fuel cell electric vehicles](#), *International Journal of Hydrogen Energy* 43 (25) (2018) 11614 – 11628, *alternative Energies for Sustainability*. doi:<https://doi.org/10.1016/j.ijhydene.2017.03.166>. URL <http://www.sciencedirect.com/science/article/pii/S0360319917311722>
- [11] M. Latroche, D. Blanchard, F. Cuevas, A. E. Kharbachi, B. C. Hauback, T. R. Jensen, P. E. de Jongh, S. Kim, N. S. Nazer, P. Ngene, S. ichi Orimo, D. B. RavnsbÅk, V. A. Yartys, Full-cell hydride-based solid-state li batteries for energy storage, *International Journal of Hydrogen Energy* 44 (15) (2019) 7875 – 7887, a special issue on hydrogen-based Energy storage.
- [12] F. Claude, M. Becherif, H. Ramadan, Experimental validation for li-ion battery modeling using extended kalman filters, *International Journal of Hydrogen Energy* 42 (40) (2017) 25509–25517.
- [13] K. Kutluay, Y. Cadirci, Y. S. Ozkazanc, I. Cadirci, A new online state-of-charge estimation and monitoring system for sealed lead-acid batteries in telecommunication power supplies, *IEEE Transactions on Industrial Electronics* 52 (5) (2005) 1315–1327. doi:[10.1109/TIE.2005.855671](https://doi.org/10.1109/TIE.2005.855671).
- [14] X. Dang, L. Yan, H. Jiang, X. Wu, H. Sun, Open-circuit voltage-based state of charge estimation of lithium-ion power battery by combining controlled auto-regressive and moving average modeling with feedforward-feedback compensation method, *International Journal of Electrical Power & Energy*

Systems 90 (2017) 27 – 36.

- [15] N. Watrin, R. Roche, H. Ostermann, B. Blunier, A. Miraoui, Multiphysical lithium-based battery model for use in state-of-charge determination, *IEEE Transactions on Vehicular Technology* 61 (8) (2012) 3420–3429.
- [16] W. Waag, S. Kabitz, D. U. Sauer, Experimental investigation of the lithium-ion battery impedance characteristic at various conditions and aging states and its influence on the application, *Applied Energy* 102 (2013) 885 – 897, special Issue on Advances in sustainable biofuel production and use - XIX International Symposium on Alcohol Fuels - ISAF.
- [17] W. Waag, D. U. Sauer, Adaptive estimation of the electromotive force of the lithium-ion battery after current interruption for an accurate state-of-charge and capacity determination, *Applied Energy* 111 (2013) 416 – 427.
- [18] W. Li, Z. Jiao, L. Du, W. Fan, Y. Zhu, [An indirect rul prognosis for lithium-ion battery under vibration stress using elman neural network](#), *International Journal of Hydrogen Energy* 44 (23) (2019) 12270 – 12276. doi:<https://doi.org/10.1016/j.ijhydene.2019.03.101>.
URL <http://www.sciencedirect.com/science/article/pii/S0360319919311073>
- [19] S. Zhang, L. Yang, X. Zhao, J. Qiang, A ga optimization for lithium-ion battery equalization based on soc estimation by nn and flc, *International Journal of Electrical Power & Energy Systems* 73 (2015) 318 – 328.
- [20] Z. Zhang, X. Cheng, Z. Lu, D. Gu, Soc estimation of lithium-ion battery pack considering balancing current, *IEEE Transactions on Power Electronics* 33 (3) (2018) 2216–2226.
- [21] J. Meng, M. Ricco, G. Luo, M. Swierczynski, D.-I. Stroe, A.-I. Stroe, R. Teodorescu, An overview and comparison of online implementable soc estimation methods for lithium-ion battery, *IEEE Transactions on Industry Applications* 54 (2) (2017) 1583–1591.
- [22] Z. Wei, C. Zou, F. Leng, B. H. Soong, K.-J. Tseng, Online model identification and state-of-charge estimate for lithium-ion battery with a recursive total least squares-based observer, *IEEE Transactions on Industrial Electronics* 65 (2) (2017) 1336–1346.
- [23] W. Zhang, L. Wang, L. Wang, C. Liao, An improved adaptive estimator for state-of-charge estimation of lithium-ion batteries, *Journal of Power Sources* 402 (2018) 422 – 433.
- [24] X. Tang, B. Liu, Z. Lv, F. Gao, Observer based battery soc estimation: Using multi-gain-switching approach, *Applied energy* 204 (2017) 1275–1283.
- [25] C. Zhang, L. Y. Wang, X. Li, W. Chen, G. G. Yin, J. Jiang, Robust and adaptive estimation of state of

- charge for lithium-ion batteries, *IEEE Transactions on Industrial Electronics* 62 (8) (2015) 4948–4957.
- [26] H. Chaoui, C. C. Ibe-Ekeocha, State of charge and state of health estimation for lithium batteries using recurrent neural networks, *IEEE Transactions on Vehicular Technology* 66 (10) (2017) 8773–8783.
- [27] J. C. Alvarez Anton, P. J. Garcia Nieto, C. Blanco Viejo, J. A. Vilan Vilan, Support vector machines used to estimate the battery state of charge, *IEEE Transactions on Power Electronics* 28 (12) (2013) 5919–5926.
- [28] J. C. A. Anton, P. J. G. Nieto, E. G. Gonzalo, J. C. V. Pérez, M. G. Vega, C. B. Viejo, A new predictive model for the state-of-charge of a high-power lithium-ion cell based on a pso-optimized multivariate adaptive regression spline approach, *IEEE Transactions on Vehicular Technology* 65 (6) (2015) 4197–4208.
- [29] K. Song, F. Li, X. Hu, L. He, W. Niu, S. Lu, T. Zhang, Multi-mode energy management strategy for fuel cell electric vehicles based on driving pattern identification using learning vector quantization neural network algorithm, *Journal of Power Sources* 389 (2018) 230 – 239.
- [30] J. C. Alvarez Anton, P. J. Garcia Nieto, E. Garcia Gonzalo, J. C. Viera Perez, M. Gonzalez Vega, C. Blanco Viejo, A new predictive model for the state-of-charge of a high-power lithium-ion cell based on a pso-optimized multivariate adaptive regression spline approach, *IEEE Transactions on Vehicular Technology* 65 (6) (2016) 4197–4208.
- [31] T. Mesbahi, F. Khenfri, N. Rizoug, K. Chaaban, P. Bartholomeus, P. L. Moigne, Dynamical modeling of li-ion batteries for electric vehicle applications based on hybrid particle swarm-nelder-mead (pso-nm) optimization algorithm, *Electric Power Systems Research* 131 (2016) 195 – 204.
- [32] N. Kumar, I. Hussain, B. Singh, B. K. Panigrahi, Single sensor-based mppt of partially shaded pv system for battery charging by using cauchy and gaussian sine cosine optimization, *IEEE Transactions on Energy Conversion* 32 (3) (2017) 983–992.
- [33] R. Chenouard, R. A. El-Sehiemy, [An interval branch and bound global optimization algorithm for parameter estimation of three photovoltaic models](#), *Energy Conversion and Management* 205 (2020) 112400. doi:<https://doi.org/10.1016/j.enconman.2019.112400>.
URL <http://www.sciencedirect.com/science/article/pii/S0196890419314074>
- [34] R. A. E. Sehiemy, F. Selim, B. Bentouati, M. Abido, [A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical-environmental operation in power systems](#), *Energy* 193 (2020) 116817. doi:<https://doi.org/10.1016/j.energy.2019.116817>.
URL <http://www.sciencedirect.com/science/article/pii/S0360544219325125>

- [35] A. A. A. El-Ela, R. A. El-Sehiemy, E. S. Ali, A.-M. Kinawy, Minimisation of voltage fluctuation resulted from renewable energy sources uncertainty in distribution systems, *IET Generation, Transmission & Distribution* 13 (12) (2019) 2339–2351.
- [36] M. Little, M. Thomson, D. Infield, Electrical integration of renewable energy into stand-alone power supplies incorporating hydrogen storage, *International Journal of Hydrogen Energy* 32 (10-11) (2007) 1582–1588.
- [37] Y. Han, W. Chen, Q. Li, H. Yang, F. Zare, Y. Zheng, Two-level energy management strategy for pv-fuel cell-battery-based dc microgrid, *International Journal of Hydrogen Energy* 44 (35) (2019) 19395–19404.
- [38] R. Lin, D. Liu, S. Xia, T. Ma, B. Dutruel, Stack shut-down strategy optimisation of proton exchange membrane fuel cell with the segment stack technology, *International Journal of Hydrogen Energy* 45 (1) (2020) 1030–1044.
- [39] G. F. Gomes, S. S. da Cunha, A. C. Ancelotti, A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates, *Engineering with Computers* (2019). doi: [10.1007/s00366-018-0620-8](https://doi.org/10.1007/s00366-018-0620-8).
- [40] M. H. Qais, H. M. Hasanien, S. Alghuwainem, Identification of electrical parameters for three-diode photovoltaic model using analytical and sunflower optimization algorithm, *Applied Energy* (2019). doi: [10.1016/j.apenergy.2019.05.013](https://doi.org/10.1016/j.apenergy.2019.05.013).
- [41] X. Lai, W. Gao, Y. Zheng, M. Ouyang, J. Li, X. Han, L. Zhou, A comparative study of global optimization methods for parameter identification of different equivalent circuit models for li-ion batteries, *Electrochimica Acta* 295 (2019) 1057 – 1066.
- [42] S. Orcioni, L. Buccolini, A. Ricci, M. Conti, Lithium-ion battery electrothermal model, parameter estimation, and simulation environment, *Energies* 10 (3) (2017) 375.
- [43] H. Rahimi-Eichi, F. Baronti, M. Chow, Online adaptive parameter identification and state-of-charge coestimation for lithium-polymer battery cells, *IEEE Transactions on Industrial Electronics* 61 (4) (2014) 2053–2061.
- [44] M. A. M. Shaheen, H. M. Hasanien, S. F. Mekhamer, H. E. A. Talaat, Optimal power flow of power systems including distributed generation units using sunflower optimization algorithm, *IEEE Access* 7 (2019) 109289–109300. doi: [10.1109/ACCESS.2019.2933489](https://doi.org/10.1109/ACCESS.2019.2933489).
- [45] N. Rizoug, R. Sadoun, T. Mesbahi, P. Bartholomeus, P. LeMoigne, Aging of high power li-ion cells during real use of electric vehicles, *IET Electrical Systems in Transportation* 7 (1) (2017) 14–22. doi: [10.1049/iet-est.2016.0012](https://doi.org/10.1049/iet-est.2016.0012).

- [46] T. Mesbahi, N. Rizoug, P. Bartholomeus, R. Sadoun, F. Khenfri, P. Le Moigne, Dynamic model of li-ion batteries incorporating electrothermal and ageing aspects for electric vehicle applications, *IEEE Transactions on Industrial Electronics* 65 (2) (2018) 1298–1305. doi:10.1109/TIE.2017.2714118.
- [47] J. Torres, R. Gonzalez, A. Gimenez, J. Lopez, Energy management strategy for plug-in hybrid electric vehicles. a comparative study, *Applied Energy* 113 (2014) 816 – 824.
- [48] A. Affanni, A. Bellini, G. Franceschini, P. Guglielmi, C. Tassoni, Battery choice and management for new-generation electric vehicles, *IEEE Transactions on Industrial Electronics* 52 (5) (2005) 1343–1349.
- [49] A. A. A. El-Ela, R. A. El-Sehiemy, A. S. Abbas, Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm, *IEEE Systems Journal* 12 (4) (2018) 3629–3636.
- [50] M. A. Algabalawy, A. Y. Abdelaziz, S. F. Mekhamer, S. H. A. Aleem, Considerations on optimal design of hybrid power generation systems using whale and sine cosine optimization algorithms, *Journal of Electrical Systems and Information Technology* 5 (3) (2018) 312–325.