Dynamical modeling and Identification of Li-ion batteries based on Squirrel Search Optimization Algorithm for Electric Vehicle Applications

Ali DALI (ali.dali.dz@gmail.com)
Renewable Energy Development Center
Tedjani MESBAHI
University of Strasbourg
Patrick BARTHOLOMEÜS
University of Lille
Khaled Chaaban
Umm al-Qura University

Research Article

Keywords: Equivalent circuit model, Electric vehicle, Li-ion battery, Squirrel Search algorithm, State of charge SOC

Posted Date: October 28th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-2195275/v1

Dynamical modeling and Identification of Li-ion batteries based on Squirrel Search Optimization Algorithm for Electric Vehicle Applications

Ali DALI[(*)], Tedjani MESBAHI[(**)], Patrick BARTHOLOMEÜS[(***)] and Khaled Chaaban[(****)]

(*) A. Dali is with Centre de Développement des Energies Renouvelables, CDER, BP 62 Route de l'Observatoire, Bouzaréah, 16340, Alger, Algérie. (e-mail: a.dali@cder.dz).
(**) T. MESBAHI is with ICube, CNRS (UMR 7357), INSA Strasbourg, University of Strasbourg, F-67000 Strasbourg, France. (e-mail: tedjani.mesbahi@insa-strasbourg.fr).
(**) P. BARTHOLOMEÜS is with Univ. Lille, Centrale Lille, Arts et Metiers ParisTech, HEI, HeSam, EA 2697, L2EP - Laboratoire d'Electrotechnique et d'Electronique de Puissance Lille, France. (e-mail: patrick.bartholomeus@centralelille.fr).
(****) K. Chaaban is with Computer science and information systems college, Umm Al-QURA University, Makkah, Saudi Arabia. (e-mail: aochaaban@uqu.edu.sa).

Abstract—**This paper presents an advanced method for modeling and parameter identification of the lithium-ion (Li-ion) battery using an experimental characterization. A comparison study between two Li-ion models and a proposed one are performed where each model parameters are identified using three different algorithms. The obtained models are then tested and validated using experimental data obtained from a real test bench.**

The identification methods are implemented using a precise nonlinear model based on electric equivalent circuit of Li-ion battery and the parameter identification process formulated as a nonlinear optimization problem. In order to compare the capability of each model to represent effectively the Li-ion battery regardless of the optimization method, three optimization algorithms are involved: Squirrel Search Algorithm (SS), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Numerical simulations along with experimental validation are performed on 20 Ah Li-ion battery. The models are compared according to the lowest fitness function levels of each algorithm and their limitation were also discussed in this paper. The obtained results show that the proposed models are able to simulate the dynamic behavior of Li-ion battery with good performances.

keywords— **Equivalent circuit model, Electric vehicle, Li-ion battery, Squirrel Search algorithm, State of charge SOC.**

I. INTRODUCTION

In 2030, almost a quarter of the sold cars will be either hybrid or fully electric, this will require a huge number of batteries. Lithium-ion (li-ion) batteries are widely used by global carmakers to power electric vehicles. The battery is a complex electrochemical system that is both nonlinear and the non-stationary [1][2]. The battery non-linearity is caused by the nonlinear relationship between the voltage recovered at the output and the current applied at the input of the battery [3][4]. The non-stationarity of the battery is due to the fact that the battery internal parameters are variable during the life cycle of the battery and also during the charge/discharge cycle [5]. For these reasons, there are many methods of modeling battery operation and each model has its own benefits and drawbacks [6][7][8][9].

In this context, several types of models can be distinguished which can be classified according to their modeling approach. The first method of modeling consists in using the laws of electrochemistry (electrochemical models) which allow, after characterization of the species, to obtain a good precision [10][11][12][13]. The second method is based on the use of physical properties associated with experimental tests (empirical models) allowing to use measurements then interpolated and possibly extrapolated [14][15][16]. A mathematical method of modeling is also used for the development of battery models. These models use numerical resolution and are based on a phenomenological approach, instead of equations or curves of physicochemical parameters [17][18][19].

In data-driven approaches, no deep physical understanding of the model is required. A "black box" model is established instead of a fully representative model for simulations. Rules are built from data: this kind of approach requires to have historical data on the system in order to predict the energetic and electrical behavior of battery cells [20][21][22][23]. The most used method in the field of engineering is based on circuit modeling (equivalent electrical circuit models) with localized constants, which allows to assign to each chemical reaction an impedance [24][25][26][27]. It is based on the analogy between the electrochemical and electrical fields. Thus, the electrical elements of the equivalent circuit allow to describe the phenomena which intervene within the system [28]. In the main, it is the requirement of the targeted application that determines the degree of complexity of the model and the modeling method. This one can favor simplicity by taking into account several simplifying assumptions, or require more performance by integrating almost all the physical and chemical properties of the battery cells.

In this study, the primary criterion for the choice of the model is the error of the fitting with the experimental provided data. This is also balanced with a pragmatic trade-off to achieve this accuracy while able to run efficiently enough to achieve complete profile predictions in a reasonable time. The role of the identification algorithm is very crucial to get very close mathematical model to the real one. Three different algorithms are involved in this study to make sure that the identified model is not affected by the type of identification method.

Genetic algorithms and particle swarm optimization techniques are often used for Li-ion parameters identification, Squirrel Search Algorithm (SS) is a new optimization technique invented in 2018 known by its capability to solve very complexes problem, it is claimed to be better than many classical metaheuristic techniques in many cases. In this context, we made a comparison study between two Li-ion models and a third proposed model, the parameters of each model are identified based on experimental data.

The rest of the manuscript is organized as follows. Section II presents the Lithium-ion battery model followed by optimization algorithms description in section III. In section IV, experimental setup is explained, then, the results and the discussion are given in section V. The paper ends with a conclusion in section VI.

II. Lithium-Ion Battery Modeling

In the literature, among the different approaches of Li-ion battery modeling, there are basically three types: experimental, electrochemical and electric circuit-based. However, the electric circuit-based models are the most suitable to represent electrical characteristics. Figure 1 shows a simple electric model based on a voltage source in series with an internal resistance and a branch of a resistance and a capacity in parallel [29]. The voltage source V_{oc} is the open circuit voltage that mainly depends on the State of charge of the Li-ion battery Soc. This later is estimated using the history of battery current, that may include also the self-discharging and current inefficiency on charge. However, in this paper, only the battery current I_b is considered. Then, the Soc is expressed as follows:

$$\begin{cases} Soc = Soc_0 - \dfrac{1}{Q_n}\displaystyle\int I_b \\ V_{oc} = b_0 + b_1 Soc \end{cases} \tag{1}$$

Soc_0 is the initial value of the Soc, b_0 and b_1 are real positive constants.

A. Model 1

The battery terminal voltage V_t is described in equation 2,

$$\begin{cases} V_t = V_r + V_{oc} + V_{rc} \\ V_r = R_0 I_b \\ V_{rc} = \dfrac{R_1}{1 + SR_1C_1} I_b \end{cases} \tag{2}$$

V_r represents the series resistance R_0 voltage and V_{rc} measures the C_1R_1voltage

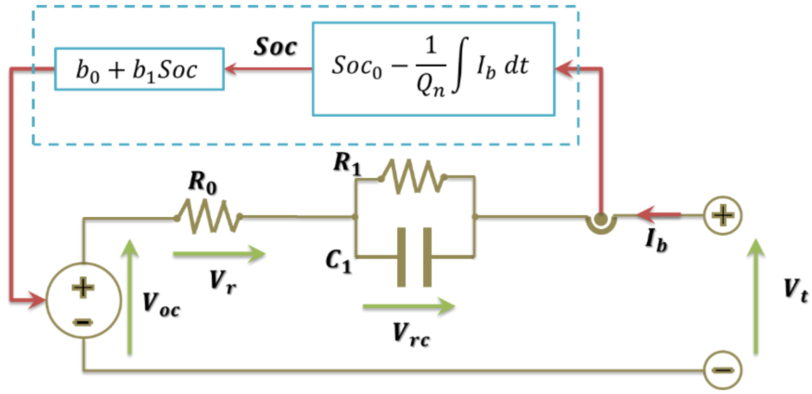


Fig. 1. Battery equivalent electric model 1.

B. Model 2

Figure 2 shows the cell equivalent model with two RC branch in order to describe both fast and slow transient response of the Li-ion battery. V_{ddl} measures the double-layer voltage (C_1R_1) which describes the fast dynamics in the battery and V_{dif} measures the diffusion voltage (C_2R_2) which describes the slower dynamics in the battery. It is given by equation (3) [29]

$$\begin{cases} V_t = V_r + V_{oc} + V_{ddl} + V_{dif} \\ V_{ddl} = \frac{R_1}{1+SR_1C_1} I_b \\ V_{dif} = \frac{R_2}{1+SR_2C_2} I_b \end{cases} \quad (3)$$

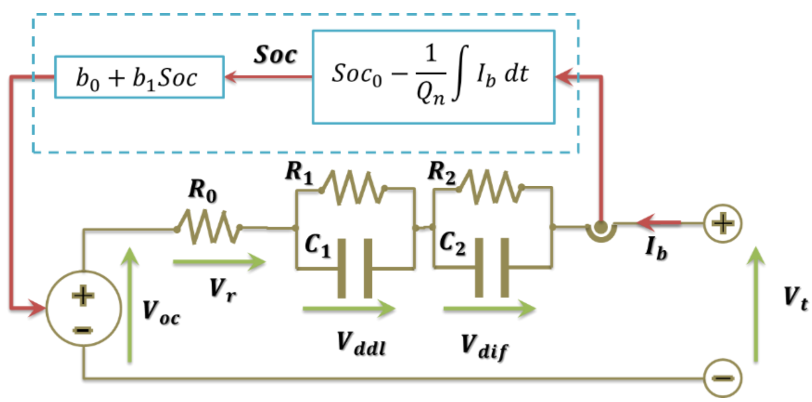


Fig. 2. Battery equivalent electric model 2.

C. Model 3

The open-circuit voltage V_{OC} is generally approximated by a linear equation of battery SOC [29]. In this paper, in order to have a better precision of the V_{oc} value, we propose that this later is approximated by equation 4:

$$V_{oc} = b_0 + b_1 e^{x_0 Soc} \quad (4)$$

x_0 is a positive real number between 0 and 1.

III. The Optimization Algorithms

A. Optimization principal

In order to identify the Li-ion battery model parameters described in the previous section, three optimization algorithms are employed. First, we define the identification error f_ε, this later measures the difference between the real and the estimated battery terminal voltage as described in figure 3. f_ε is the cost function that should be minimized so that the estimated voltage reached the real one. The process of optimization updates in each step the battery parameters in order to minimize the cost function.

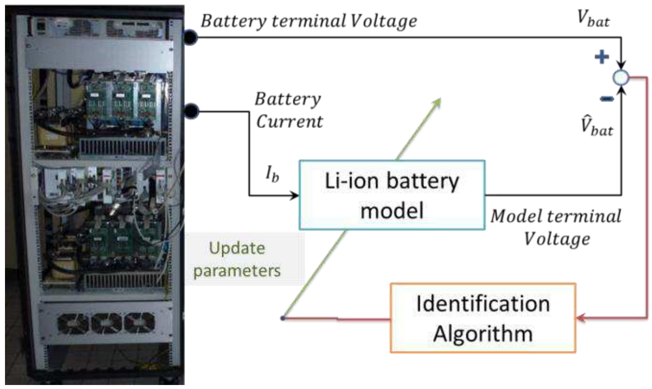


Fig. 3. Parameters identification principal

B. PSO Algorithm

This particle swarm optimization algorithm is inspired by the behavior of animal swarm, the aim of this later is to reached an optimal position, each particle (i) of the (N_p) particles of this swarm update its position at each step to reach the optimal position. The new position of each particle is a combination of its actual position vector $(\boldsymbol{z}_i)$, movement velocity vector $(\boldsymbol{v}_i)$, and best position $(\boldsymbol{p}_{best,i})$, and the global best position $(\boldsymbol{g}_{best})$.

The i^{th} particle update its position according to equation (5) [30]:

$$\boldsymbol{z}_i^{k+1} = \boldsymbol{z}_i^k + \boldsymbol{v}_i^{k+1} \quad \text{for} \quad i = 1,2,\cdots,N_p \qquad (5)$$

and the update iteration velocity at this iteration is [30]:

$$\begin{aligned}\boldsymbol{v}_i^{k+1} = \omega \boldsymbol{v}_i^k &+ c_1 r_1 (\boldsymbol{p}_{best,i} - \boldsymbol{z}_i^k) \\ &+ c_2 r_2 (\boldsymbol{g}_{best} - \boldsymbol{z}_i^k) \qquad (6) \\ \text{for} \quad i &= 1,2,\cdots,N_p\end{aligned}$$

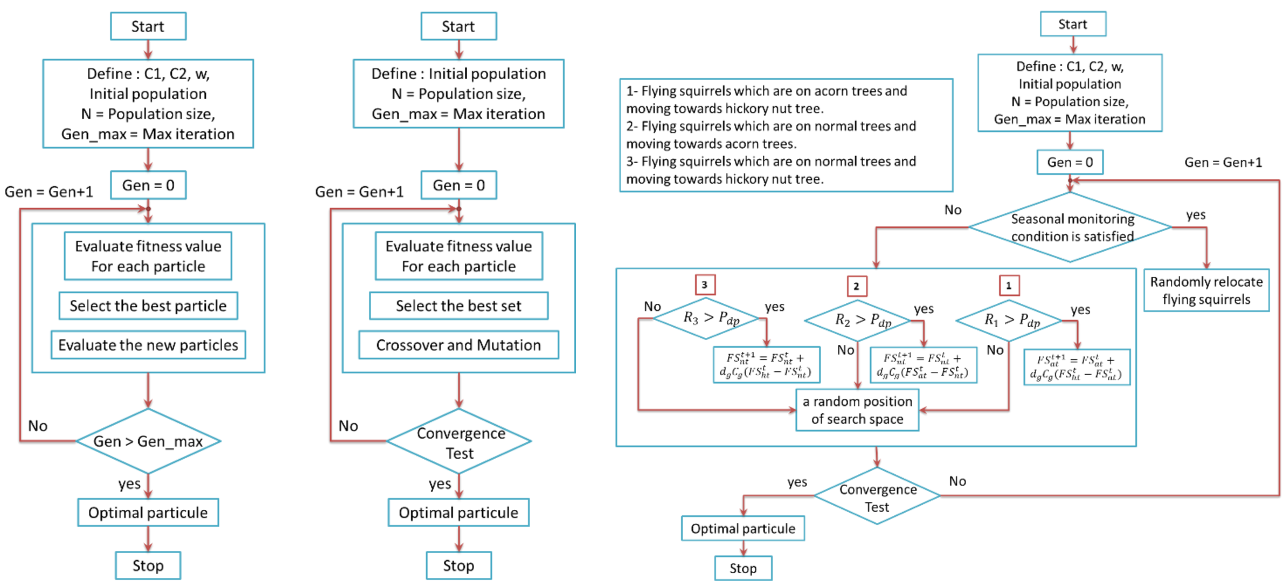
The parameter ω represents the inertia weight that fixes the propagation movement, the parameters c_1 and c_2 are respectively the cognitive coefficient and the social coefficient of all the particles, while r_1 and r_2 are random variables between 0 and 1.

The cost function is then selected as the Integral Absolute-value of the Error (IAE) as follows:

$$IAE = \frac{1}{N}\sum_{1}^{N}\frac{\left(V_{bat}(t) - V_c(t)\right)^2}{\left(max(V_c)\right)^2} \qquad (7)$$

where N is the total number of samples.

The different steps used in GA, PSO and SS-based tuning of the proposed approach are illustrated in Figure 4.



(a) (b) (c)

Fig. 4. Block diagram of: (a) PSO, (b) GA and (c) SS algorithms.

C. Genetic algorithm

The main idea of the Genetic algorithm (GA) is that a population of individuals, where each one is a set of parameters, the best individual is the ones that minimize the cost function, the other are eliminated in the next step of the algorithm. The remaining particles became the new population after the operation of crossover and mutation, the process continue until a stop criterion is reached [31]. Figure 4-b shows the steps of the algorithm.

D. Squirrel search algorithm

Squirrel search algorithm (SSA) is inspired from the behavior of southern flying squirrels [32] when they are looking for food, the movement of such squirrels is called gliding, this mechanism is also known for small mammals especially when the distances are long. The SSA mathematically models this behavior to realize the process of optimization. SSA starts with random initial location of N flying squirrels. The location of i^{th} flying squirrel FS can be specified by a vector in d dimensional search space $FS_i = [FS_{i,1}\ FS_{i,2}\ ...\ FS_{i,d}]$. The FS vectors are initialized using equation (8).

$$FS_i = FS_L + U(0,1) \times (FS_U - FS_L) \qquad (8)$$

where FS_L and FS_U are lower and upper bounds respectively and $U(0,1)$ is a uniformly distributed random number in the range [0, 1].

After that, the fitness values of each flying squirrel are calculated and the one with minimal fitness value is declared on the "hickory nut tree (ht)". The next best flying squirrels (three for this paper) are considered to be on "the acorn nuts trees (at)" and they are assumed to move towards hickory nut tree. The remaining flying squirrels are supposed to be on "normal trees (nt)".

In each step of the algorithm, the squirrels will proceed to acorn nut trees but they are affected by the presence of predators. This behavior is modelled by employing the location updating mechanism with predator presence probability (P_{dp}). Then, the dynamic foraging behavior is modelled as follows:

Case 1: Flying squirrels which are on acorn nut trees (FS_{at}) move towards hickory nut tree. In this case, the new location is obtained as follows:

$$FS_{at}^{t+1} = \begin{cases} FS_{at}^{t} + d_g\, C_g\, (FS_{ht}^{t} - FS_{at}^{t}) & R_1 \geq P_{dp} \\ \text{Random location} & \text{otherwise} \end{cases} \qquad (9)$$

Case 2: Flying squirrels on normal trees (FSnt) may move towards acorn nut trees to fulfill their daily energy needs. In this case, new location of squirrels can be obtained as follows:

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g\, C_g\, (FS_{at}^{t} - FS_{nt}^{t}) & R_2 \geq P_{dp} \\ \text{Random location} & \text{otherwise} \end{cases} \qquad (10)$$

Case 3: when the squirrels on normal trees consume the totality of acorn nuts, they may change their location towards hickory nut to store hickory nuts, the goal is to use these hickory nuts later. The new location of squirrels is then expressed as follows

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g\, C_g\, (FS_{ht}^{t} - FS_{nt}^{t}) & R_3 \geq P_{dp} \\ \text{Random location} & \text{otherwise} \end{cases} \qquad (11)$$

where dg is a random distance, where R_1, R_2 and R_3 are random numbers in the range of [0, 1], FS_{ht} is the location of flying squirrel that reached hickory nut tree and t denotes the current iteration. The balance between exploration and exploitation is achieved with the help of gliding constant G_c. In this work, the value of G_c is considered as 1.9.

Seasonal monitoring condition

Seasonal changes disturb the searching activity of flying squirrels because of weather changes [32]. Hence, this change may be explored to prevents the algorithm from being trapped in local optimal solutions.

a. First calculate the seasonal constant (Sc) using Eq. (12)

$$S_c^t = \sqrt{\sum_{k=1}^{d}\left(FS_{at,k}^t - FS_{kt,k}\right)^2} \qquad (12)$$

where t = 1, 2, 3.

b. Check the seasonal monitoring condition i.e., $S_c^t < S_{min}$ where S_{min} is the minimum value of seasonal constant computed as:

$$S_c^t = \sqrt{\sum_{k=1}^{d}\left(FS_{at,k}^t - FS_{kt,k}\right)^2} \qquad (13)$$

where t and tm are respectively the current and maximum iteration values. The S_{min} fixes the exploration and exploitation of the algorithm. The exploration increases proportionally with the value of S_{min} , whereas, the exploitation is the opposite.

c. Check the seasonal monitoring condition i.e., $S_c^t < S_{min}$ where S_{min} is the minimum value of seasonal constant computed as:

$$S_{min} = \frac{10E^{-6}}{365^t/(t_m/2.5)} \qquad (14)$$

The relocation of such flying squirrels is modelled through the following equation:

$$\{FS_{nt}^{new} = FS_L + L\acute{e}vy(n) \times (FS_U - FS_L) \qquad (15)$$

IV. Experimental Setup

The battery used in this study is a nanophosphate technology cylinder cell. This battery is commercialized by A123 manufacture under the references A123AHR32113M1 Ultra-B. The nominal, maximum, and cutoff voltages of the battery under study are 3.3, 3.6, and 2.0 V, respectively. The maximum continuous discharge current is 200 A while recommended fast charge is 65 A to 3.6V. It can support a pulse discharge of 350 A at 25 °C during less than 10 s. The operation temperature range is comprised between [-30–65] C and absolute maximum cell temperature is 85 °C.

A test bench is used to carry out accelerated cycling aging tests while trying to be as close as possible to the electric vehicle applications. The aim of this bench is to characterize the energetic and electrical behavior of battery cells for high current applications (500 A). It allows to characterize up to four series of samples of batteries in cycling according to the number of charge and discharge cycles carried out. The particularity of this bench is to be modular, that is to say to be able to adapt to a great number of storage systems by carrying out the minimum of software or hardware modifications. The bench is composed of four channels of cycling and measurement with a capacity in voltage and current of 30V and 500A (up to 600A under some conditions). The channels work in pairs and in opposition of cycle, the objective being to limit the power peaks to be brought when a great number of channels is used. The average power absorbed by the bench is 3,5KW with peaks up to ±16kW. This power can be further increased by the principle of power opposition when two channels are used. The laboratory test bench is shown in Figure 5.

Fig. 5. Laboratory test bench.

V. Results and Discussion

In this section, the parameters of the Li-ion battery are identified using the three algorithms, the search range are listed in Table I and the algorithms parameters are listed in table II, III and IV respectively.

TABLE I

SEARCH RANGE OF THE LI-ION BATTERY PARAMETERS

Battery parameters	Search range	
	Min	**Max**
$\boldsymbol{b_0}$	2	4
$\boldsymbol{b_1}$	0	0.8
$\boldsymbol{R_0}$	0	0.01
$\boldsymbol{R_1}$	10^{-4}	10^{-2}
$\boldsymbol{C_1}$	10^{+2}	10^{+6}
$\boldsymbol{R_2}$	10^{-4}	10^{-2}
$\boldsymbol{C_2}$	10^{+2}	10^{+6}
$\boldsymbol{x_0}$	-5	5

TABLE II

GENETIC ALGORITHMS PARAMETERS

Parameter	Value
Population size	200
Number of iterations	200
Selection	Uniform stochastic
Crossover	Random
Mutation	Gaussian

TABLE III

PSO ALGORITHM PARAMETERS

Parameter	Value
Population size	200
Number of iterations	200
social parameter C1	1
cognitive parameter C2	3
Speed factor w	0.8

TABLE IV

SS ALGORITHM PARAMETERS

Parameter	Value
Population size	200
Number of iterations	200
Pdp	0.5

dg	0.8
Gc	1.9

The optimal parameters obtained by SS algorithm are summarized in table V.

TABLE V

THE OPTIMAL PARAMETERS

b_0	b_1	R_0	R_1	C_1	R_2	C_2	x_0
3.138	0.04705	0.001328	0.0001271	932570.8	0.0006368	8513.54	1.34

The simulation results obtained by using model 1 compared with those recorded in the experimental data are illustrated in figure 6. The results for Model 2 and 3 are shown in figure 7 and 8 respectively.

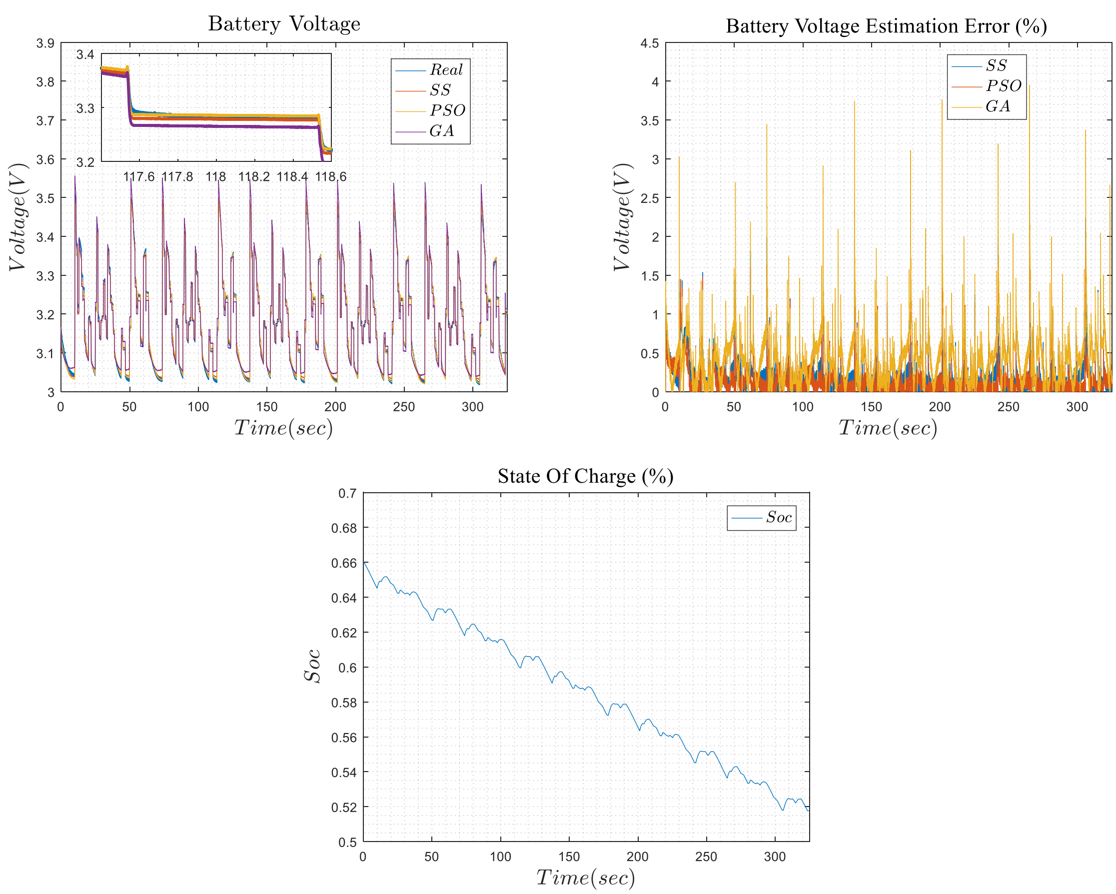


Fig. 6. Simulation results for model 1

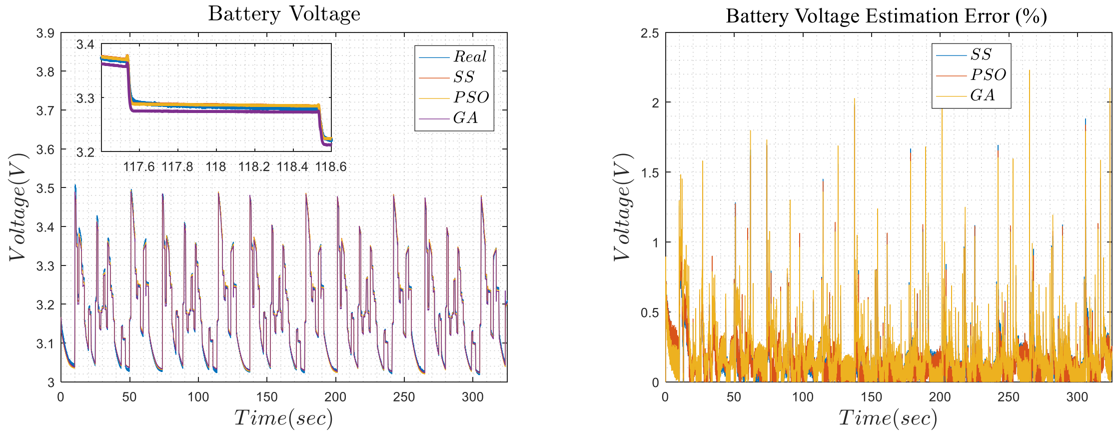


Fig. 7. Simulation results for model 2

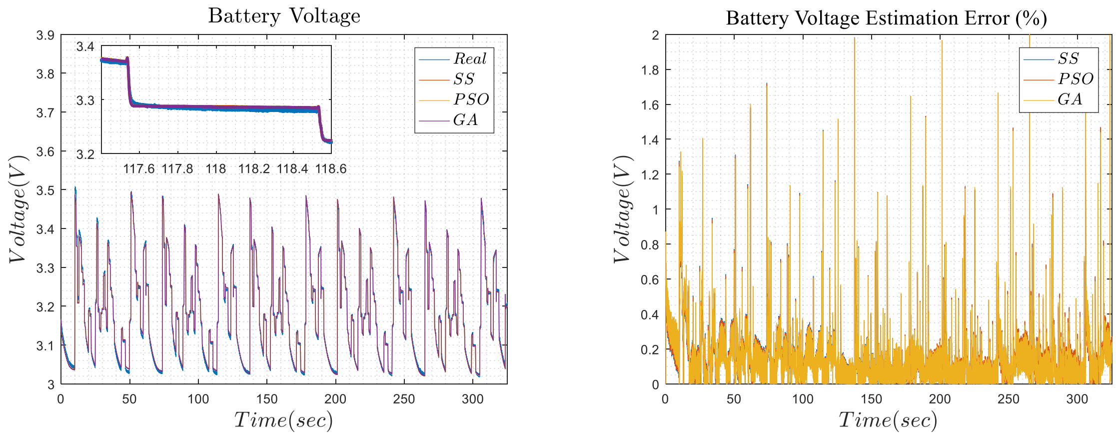


Fig. 8. Simulation results for model 3

The relative error is calculated as follows

$$Err_{V_{bat}}(\%) = \left|\frac{\hat{V}_{bat} - V_{ex}}{V_{ex}^{max}}\right| \times 100 \qquad (16)$$

The cost function is given by

$$Error = \sqrt{\frac{1}{N}\sum\left(\frac{\hat{V}_{bat} - V_{ex}}{V_{ex}^{max}}\right)^2} \qquad (17)$$

The cost functions of the three model are listed in table VI

TABLE VI

COST FUNCTION

Cost function	SS	PSO	GA
Model 1	0.00238	**0.00187**	0.00514
Model 2	**0.00179**	0.00180	0.00226
Model 3	**0.00178**	**0.00178**	0.00179

According to the obtained results, Model 3 gave the better results regardless to the algorithm used for identification. On the other hand, SSA and PSO algorithms show a good better capability to identify the battery parameters.

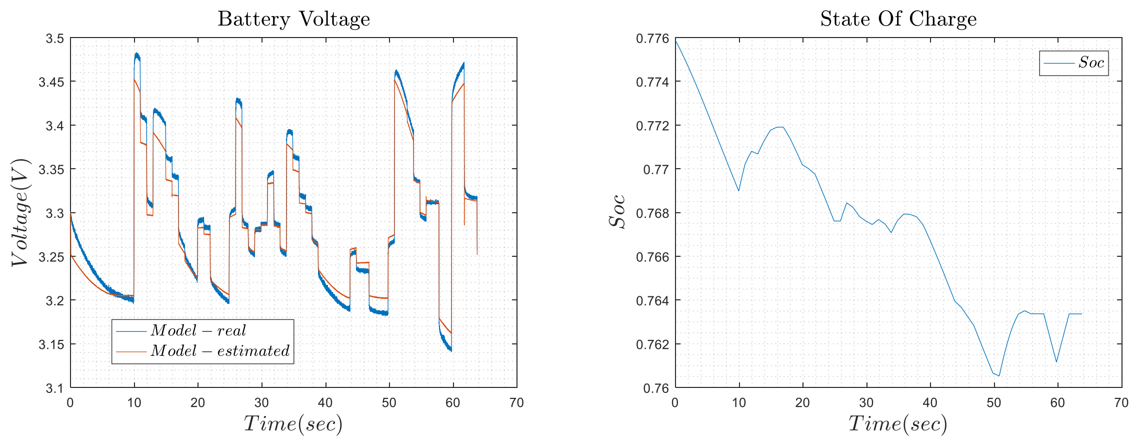


Fig. 9. Simulation results for validation Test 1

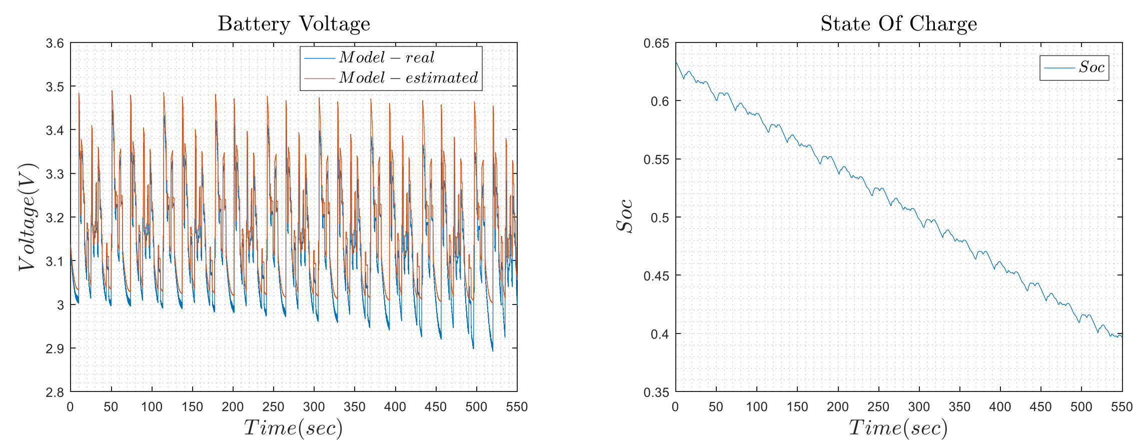


Fig. 10. Simulation results for validation Test 2

To validate the obtained results, we performed two other experimental testes in deferent environmental conditions such as temperature. The results are shows in in figure 9 and 10 respectively. The model 3 used for the simulation is not extremely affected. The battery current obtained by simulation is closed to the current issued from the experimental data.

VI. Conclusion

This work has considered the important problem of the batteries modeling and parameters identification. A complete representative model has been first developed for Li-ion battery as well as two other classical models. These models are basically composed of an open circuit voltage, a serial resistance and a RC impedance. The third model has been improved by taking into account the nonlinear relationship between the V_{oc} and the battery SOC.

Though, because of the complexity and nonlinearity of the battery model, meta-heuristic optimization algorithms have been used in order to obtain the optimal parameters of battery models. The aim of such approach is to find the optimal parameters regardless of the nature of the identification algorithm.

The developed model presents an improvement compared to the other two conventional ones; this result has been validated using experimental data through dynamic charge/discharge cycle. future work will focus on improving the battery model by introducing other physical phenomena, especially the temperature and aging.

Declarations

Ethical Approval

This declaration is “not applicable”.

Competing interests

We declare that the authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Authors' contributions

DALI and MESBAHI performed the simulations and wrote the main manuscript, BARTHOLOMEÜS and CHAABAN contributed to write the main manuscript.

Funding

This declaration is “not applicable”.

Availability of data and materials

All of the material is owned by the authors and no permissions are required.

REFERENCES

[1] T. Mesbahi, P. Bartholomeus, N. Rizoug, R. Sadoun, F. Khenfri, and P. Le Moigne, “Advanced Model of Hybrid Energy Storage System Integrating Lithium-Ion Battery and Supercapacitor for Electric Vehicle Applications,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 5, pp. 3962–3972, May 2021.

[2] T. Mesbahi *et al.*, “A stand-alone wind power supply with a Li-ion battery energy storage system,” *Renew. Sustain. Energy Rev.*, vol. 40, 2014.

[3] N. El Ghossein, A. Sari, and P. Venet, “Nonlinear Capacitance Evolution of Lithium-Ion Capacitors Based on Frequency-and Time-Domain Measurements,” *IEEE Trans. Power Electron.*, 2018.

[4] T. Mesbahi, R. B. Sugrañes, R. Bakri, and P. Bartholomeüs, “Coupled electro-thermal modeling of lithium-ion batteries for electric vehicle application,” *J. Energy Storage*, vol. 35, 2021.

[5] S. F. Schuster *et al.*, “Nonlinear aging characteristics of lithium-ion cells under different operational conditions,” *J. Energy Storage*, vol. 1, no. 1, 2015.

[6] M. Conte, F. V. Conte, I. D. Bloom, K. Morita, T. Ikeya, and J. R. Belt, “Ageing testing procedures on lithium batteries in an international collaboration context,” *World Electr. Veh. J.*, vol. 4, no. 1, pp. 335–346, 2011.

[7] J. E. Harlow *et al.*, “A Wide Range of Testing Results on an Excellent Lithium-Ion Cell Chemistry to be used as Benchmarks for New Battery Technologies,” *J. Electrochem. Soc.*, vol. 166, no. 13, pp. A3031–A3044, 2019.

[8] T. L. Vincent, P. J. Weddle, and G. Tang, “System theoretic analysis of battery charging optimization,” *J. Energy Storage*, vol. 14, pp. 168–178, 2017.

[9] D. Chen, J. Jiang, X. Li, Z. Wang, and W. Zhang, “Modeling of a pouch lithium ion battery using a distributed parameter equivalent circuit for internal non-uniformity analysis,” *Energies*, vol. 9, no. 11, 2016.

[10] C. R. Birkl, E. McTurk, M. R. Roberts, P. G. Bruce, and D. A. Howey, “A Parametric Open Circuit Voltage Model for Lithium Ion Batteries,” *J. Electrochem. Soc.*, vol. 162, no. 12, 2015.

[11] M. B. Pinson and M. Z. Bazant, “Theory of SEI Formation in Rechargeable Batteries: Capacity Fade, Accelerated Aging and Lifetime Prediction,” *J. Electrochem. Soc.*, vol. 160, no. 2, 2013.

[12] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, “A review on lithium-ion battery ageing mechanisms and estimations for automotive applications,” *Journal of Power Sources*, vol. 241. 2013.

[13] X. Lin *et al.*, “A lumped-parameter electro-thermal model for cylindrical batteries,” *J. Power Sources*, vol. 257, pp. 1–11, 2014.

[14] E. Samadani *et al.*, “Empirical Modeling of Lithium-ion Batteries Based on Electrochemical Impedance Spectroscopy Tests,” *Electrochim. Acta*, vol. 160, pp. 169–177, Apr. 2015.

[15] S. Buller, *Impedance-Based Simulation Models for Energy Storage Devices in Advanced Automotive Power Systems*. 2003.

[16] R. . Wright *et al.*, “Calendar- and cycle-life studies of advanced technology development program generation 1 lithium-ion batteries,” *J. Power Sources*, vol. 110, no. 2, pp. 445–470, 2002.

[17] H. Al Jed, A. Mieze, J.-M. Vinassa, and R. Simon, “Mathematical modeling of aging factors for Li-ion battery cells,” in *2010 IEEE Vehicle Power and Propulsion Conference*, 2010, pp. 1–4.

[18] H. Abdollahzadeh and M. Jazaeri, “Phase- and sequence-domain static models equivalent to long double-circuit transmission lines,” *Appl. Math. Model.*, vol. 45, pp. 965–981, 2017.

[19] K. S. Hariharan, P. Tagade, and S. Ramachandran, *Mathematical Modeling of Lithium Batteries From Electrochemical Models to State Estimator Algorithms*, no. 9783319035260. 2018.

[20] I. Jorge, A. Samet, T. Mesbahi, and R. Bone, “New ANN results on a major benchmark for the prediction of RUL of Lithium Ion batteries in electric vehicles,” *Proc. - 19th IEEE Int. Conf. Mach. Learn. Appl. ICMLA 2020*, pp. 1246–1253, Dec. 2020.

[21] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, “Machine Learning Approaches for EV Charging Behavior: A Review,” *IEEE Access*, vol. 8, pp. 168980–168993, 2020.

[22] C. Vidal, P. Malysz, P. Kollmeyer, and A. Emadi, “Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art,” *IEEE Access*, vol. 8, pp. 52796–52814, 2020.

[23] W. Li, N. Sengupta, P. Dechent, D. Howey, A. Annaswamy, and D. U. Sauer, “One-shot battery degradation trajectory prediction with deep learning,” *J. Power Sources*, vol. 506, p. 230024, Sep. 2021.

[24] A. Abdollahi *et al.*, “Optimal charging for general equivalent electrical battery model, and battery life management,” *J. Energy Storage*, vol. 9, pp. 47–58, 2017.

[25] A. Seaman, T.-S. Dao, and J. McPhee, “A survey of mathematics-based equivalent-circuit and electrochemical battery models for hybrid and electric vehicle simulation,” *J. Power Sources*, vol. 256, pp. 410–423, Jun. 2014.

[26] N. Devillers, M. C. Péra, S. Jemei, F. Gustin, and D. Bienaimé, “Complementary characterization methods for Lithium-ion Polymer secondary battery modeling,” *Int. J. Electr. Power Energy Syst.*, vol. 67, pp. 168–178, 2015.

[27] T. Mesbahi, N. Rizoug, F. Khenfri, P. Bartholomeüs, and P. Le Moigne, “Dynamical modelling and emulation of Li-ion batteries–supercapacitors hybrid power supply for electric vehicle applications,” *IET Electr. Syst. Transp.*, vol. 7, no. 2, pp. 161–169, Jun. 2017.

[28] T. Mesbahi, N. Rizoug, P. Bartholomeus, R. Sadoun, F. Khenfri, and P. Le Moigne, “Dynamic Model of Li-Ion Batteries Incorporating Electrothermal and Ageing Aspects for Electric Vehicle Applications,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1298–1305, Feb. 2018.

[29] Mesbahi, Tedjani, et al. "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.

[30] Kennedy, J. (2010). Particle swarm optimization. Encyclopedia of machine learning, 760-766.

[31] Anula Khare et al. “A review of particle swarm optimization and its applications in Solar Photovoltaic system”. Applied Soft Computing 13 (2013) 2997–3006.

[32] Jain, Mohit, Vijander Singh, and Asha Rani. *"A novel nature-inspired algorithm for optimization: Squirrel search algorithm."* Swarm and evolutionary computation 44 (2019): 148-175.