

## An electric circuit model for a lithium-ion battery cell based on automotive drive cycles measurements

Jaouad Khalfi<sup>1</sup>, Najib Boumaaz<sup>2</sup>, Abdallah Soulmani<sup>3</sup>, El Mehdi Laadissi<sup>4</sup>

<sup>1,2,3</sup>Department of Physics, Laboratory of Electrical Systems, Energy Efficiency and Telecommunications,  
Faculty of Sciences and Technology, Cadi Ayyad University, Marrakech, Morocco

<sup>4</sup>Laboratory of Engineering Sciences for Energy (LabSIPE), National School of Applied Sciences,  
Chouaib Doukkali University, El Jadida, Morocco

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### ABSTRACT

The on-board energy storage system plays a key role in electric vehicles since it directly affects their performance and autonomy. The lithium-ion battery offers satisfactory characteristics that make electric vehicles competitive with conventional ones. This article focuses on modeling and estimating the parameters of the lithium-ion battery cell when used in different electric vehicle drive cycles and styles. The model consists of an equivalent electrical circuit based on a second-order Thevenin model. To identify the parameters of the model, two algorithms were tested: Trust-Region-Reflective and Levenberg-Marquardt. To account for the dynamic behavior of the battery cell in an electric vehicle, this identification is based on measurement data that represents the actual use of the battery in different conditions and driving styles. Finally, the model is validated by comparing simulation results to measurements using the mean square error (MSE) as model performance criteria for the driving cycles (UDDS, LA-92, US06, neural network (NN), and HWFET). The results demonstrate interesting performance mostly for the driving cycles (UDDS and LA-92). This confirms that the model developed is the best solution to be integrated in a battery management system of an electric vehicle.

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### Corresponding Author:

Jaouad Khalfi

Department of Physics, Laboratory of Electrical Systems, Energy Efficiency and Telecommunications

Faculty of Sciences and Technology

Cadi Ayyad University

40000 Marrakech, Morocco

Email: jaouad.khalfi@gmail.com

## 1. INTRODUCTION

Among the solutions to the problems generated by mobility, the electrification of vehicles is increasingly considered by public and private stakeholders [1]. Electric and hybrid vehicles can reduce our fossil fuel consumption [2-5]. In this type of vehicle, the most sensitive component is the battery. This article aims to study battery cell performance in electric vehicles. The study focuses on lithium-ion accumulators, which have the most promising properties on the market among different battery technologies, particularly in terms of energy and mass power [6-11]. It is currently the best candidate for energy storage in electric vehicles [12, 13].

To achieve the aim of this study, it is first necessary to have a battery cell model that not only describes the electrical behavior, but also considers the thermal behavior of the battery cell. These elements directly affect vehicle performance [14]. Moreover, the model of the battery cell must consist of the

minimum necessary elements to minimize simulation time without sacrificing accuracy in order to be integrated into a battery management system.

The simplicity of the model identification must also satisfy these requirements [15]. In electric vehicles, precise modeling and simulation of a battery to examine the performance of the storage system is required. A model can be defined as a simplified mathematical representation of a battery. The models make it possible to predict the behavior of a battery and to observe phenomena that are often impossible to measure in real use in electric vehicles. For example, a model can allow us to simulate several years of the life cycle of a storage system in a few minutes. This obviates having to build physical prototypes each time and to conduct expensive experiments. Predictive engineering necessitates developing a model that considers aspects of interest as closely as possible to reality to answer certain engineering questions.

Battery modeling involves several categories of modeling: Physicochemical modeling, "black box" modeling, energy modeling, and electrical modeling. Many researchers conduct electrical modeling using equivalent electrical circuits. In the modeling of the equivalent electrical circuit, the electrical characteristics of the battery are taken into account and passive linear elements are used. Such models are easy to understand and their level of detail depends on the problem to be solved.

The model identification of electrochemical accumulators is made by tests on the battery cell. It comprises selecting a technique that best suits the chosen model. Because it must consider the accumulator behavior during transient and permanent phases of operation, it is useful to use identification techniques that aim to study the accumulator dynamics in the time-type domain that corresponds to the nature of the model. The main objective of this article is to develop an equivalent electrical circuit model [16] for a Li-ion battery cell intended for use in electric vehicles. Modeling is based on measurements during different driving cycles and different driving styles of electric vehicles to widen the range of use of the proposed model.

The identification of the proposed model and the estimation of its parameters must be determined using an algorithm that does not require multiple iterations, which implies a reduced identification time. Therefore, this paper compares two algorithms (Trust-Region-Reflective and Levenberg-Marquardt) using the criteria of the mean squared error (MSE) and the number of iterations. The results show that the Levenberg-Marquardt algorithm performs better in terms of the number of iterations.

The model was validated using different driving cycles that represent different conditions and driving styles of an electric vehicle on a highway, a rural and an urban road as described in section 4 (UDDS, LA-92, US06, neural network and HWFET) based on the mean squared error (MSE) as model performance criteria. The phase of model validation offers interesting results mostly for the LA-92 and UDDS drive cycles. This paper is divided into seven parts. After an introduction in the first part, the second part presents a bibliographic modeling of lithium batteries. The third part demonstrates the electrical modeling through equivalent electrical circuits. In the fourth part, we focus on parameter identification and experimental data used for estimation and validation of the equivalent electrical circuit model proposed for the NCR18650PF Panasonic lithium-ion battery cell. The fifth part presents a battery cell parameter identification procedure using the parameter estimation toolbox and a battery cell second order equivalent electrical circuit model. The sixth part presents the results of parameter identification of the battery cell electrical equivalent model. Thereafter, we present the model validation results and their interpretation. Finally, a conclusion summarizes the work.

## 2. ELECTRICAL MODELING BY EQUIVALENT ELECTRICAL CIRCUITS

The simulation is essential to study the accumulator's behavior in the context of a defined use, such as that of electric and hybrid vehicles. The relevance of the results obtained depends on the quality and choice of the model. The modeling challenge is, therefore, to develop models that offer both low calculation time and accuracy levels that are relative to the application requirements. If obtaining a summary representation of the behavior of batteries is easy, accounting for the true electrochemical mechanisms in extreme conditions is very complex and is obtained at the expense of simplicity and the calculation time of the model. A good choice is not necessarily based on the accuracy of the model, but rather on a compromise between accuracy, simplicity, computation time, or ease of integration into a global system. Different modeling approaches exist: physicochemical modeling [17, 18], "black box" modeling [19-21], energy modeling, electrical modeling, and through the use of equivalent electrical circuits.

Modeling by equivalent electrical circuit is widely used in the field of electrical engineering because it focuses on a description of the battery's electrical behavior. This type of modeling has been selected for this work for several reasons. First, it is relatively simple to implement, does not require a substantial calculation for the simulations, and the level of precision is acceptable. Furthermore, the identification of the parameters is not too restrictive. For example, in the time domain, several characteristic tests make it possible

to determine all the model parameters. Finally, this type of model is easily integrable into a global model of battery management systems [22, 23].

The models that take the form of equivalent electrical circuits can be classified into two groups, depending on whether they use electrochemical impedance elements. In this part, the models consist only of electrical elements, which include the source of voltage, resistances, and capacitances. The convention adopted to define the sign of the current of the battery ( $I_b$ ) is that of a battery discharge.

The simple electric model see in Figure 1 consists of two elements: a voltage source  $U_{oc}$ , which represents the voltage at rest, and a resistor  $R_0$ , which indicates the ohmic voltage drop of the battery cell. The values of these elements can be modified according to other parameters, such as the state of charge, the current value (or its direction), the temperature, and the lifetime. This model is widely used for quick dimensioning or to offer an initial view of simulations. However, many phenomena are overshadowed, which makes it difficult to achieve acceptable accuracy for many applications.

To improve this model, an RC dipole is inserted, which leads to a first order model [24-27] of Figure 2. It comprises an ideal source voltage  $U_{oc}$ , an internal resistance  $R_0$ , a capacitor  $C_1$ , which represents the polarization of the metal plates of the accumulator, and an overvoltage resistor  $R_1$  that is due to the contact of the plates with the electrolyte [28, 29]. In this model, the elements of the circuit are often considered constant, but in reality, their values vary according to the state of charge, the temperature, and the rate of discharge [30].

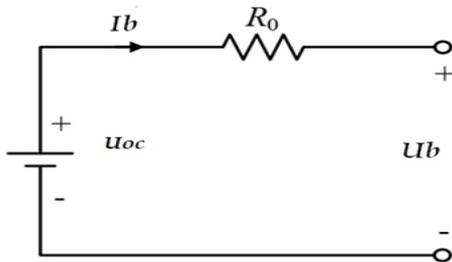


Figure 1. Simple model of a battery

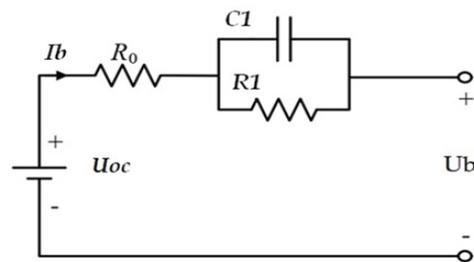


Figure 2. First order model of a battery

To take into account the dynamic polarization and electric double phenomenon response, the second order Thevenin model is introduced [31, 32] Figure 3. This model consists of an ideal voltage source  $U_{oc}$  in series with an internal resistance  $R_0$  and two RC dipoles; the first one consists of  $C_1$  and  $R_1$ , which successively represent the capacitance and the resistance of electrochemical polarization, while the second dipole includes elements  $C_2$  and  $R_2$ , which successively represent the capacitance and the concentration resistance [33, 34]. This model is adopted for this study.

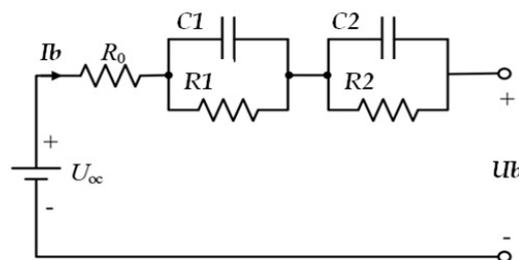


Figure 3. Second order model of a battery

### 3. PARAMETER IDENTIFICATION AND EXPERIMENTAL DATA

The electrochemical behavior of lithium-ion cells is influenced by the temperature variation [35] and the state of charge (SOC). As this work only addresses the electrical model, the temperature of the battery cell is maintained constant at an ambient temperature of 25 °C. It is then possible to study the dependence of the parameters of the battery cell model on the state of charge.

The parameters to be identified are the voltage  $U_{oc}$ , the resistors  $R_0$ ,  $R_1$ ,  $R_2$  and the capacitors  $C_1$  and  $C_2$ . To identify these parameters, we used the Simscape language integrated with the MATLAB/Simulink environment. Using this language, we realized the model presented as shown in Figure 4 based on the initial conditions of the battery, the temperature, the current profile, and the evolution of the voltage. Indeed, the SOC can be calculated using its initial value and the current value, which is, in turn, used in the blocks of capacities and resistances.

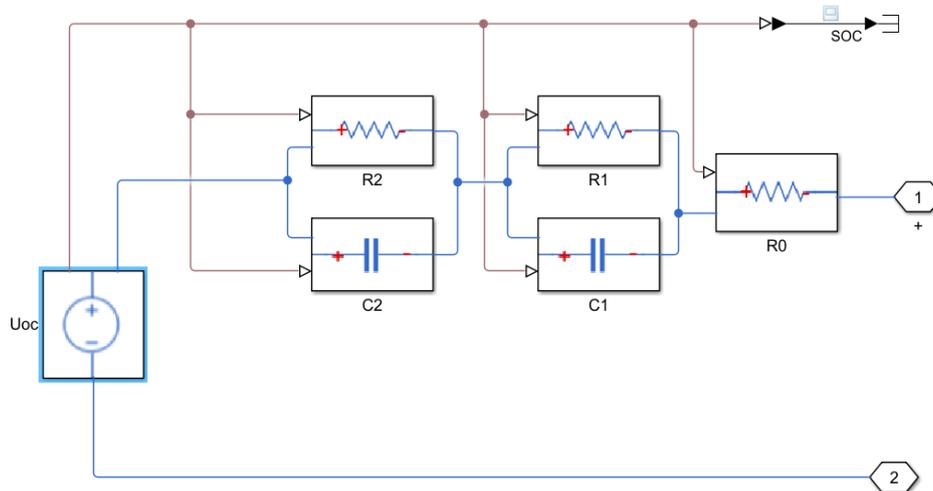


Figure 4. Battery cell model (second order)

The parameters of the model are identified by applying the nonlinear least squares method with the Levenberg-Marquardt and Trust-Region-Reflective algorithms to measurements. In the context of this article, experimental tests on the battery cell aim to identify the model of the chosen battery, to estimate its parameters, and to validate the model and the battery estimated parameters. Moreover, to perform measurements, we focus on the specific case of electric vehicles exclusively powered by a battery.

Identification procedures are applied to the elements tested under different conditions to allow modeling the battery over the entire zone of use. The identification is based on the exploitation of the data measured and recorded during a driving cycle process of an electric vehicle, as they are more representative of the real conditions of use experienced by lithium-ion cells in an electric vehicle. This expands the range of use of the proposed model in electric vehicles on highways and rural and urban roads. To our knowledge, this approach is rarely adopted in this type of problem. A driving cycle is a series of data representing the speed of the electric vehicle as a function of time. It aims to simulate the battery cell to predict its performance when used in an electric vehicle. The driving cycles used for measurements are defined as [36]:

- LA-92: The California Unified cycle, also known as the unified cycle driving schedule (UCDS). LA-92 is a chassis-dynamometer driving schedule for light-duty vehicles; it was developed in 1992 by the California air resources board (CARB).
- US06: It addresses the need for aggressive, high-acceleration and/or high-speed driving behavior, rapid speed fluctuations, and driving behavior following startup.
- UDDS: The urban dynamo driving schedule (UDDS) is the standard driving cycle for the certification of passenger vehicles and light-duty trucks.
- HWFET: The highway fuel economy test simulates interstate rural and highway driving conditions.
- Neural network: This drive cycle consists of a combination of portions of LA92 and US06 drive cycles, and it was designed to provide additional dynamics that may be useful for training neural networks.

In our case, the battery cell under test is a Panasonic 18650 battery cell with a lithium nickel cobalt aluminum oxide ( $\text{LiNiCoAlO}_2$  or NCA) chemistry [37, 38] and the electric vehicle is a Ford F150 truck [39] with a 35-kWh battery pack scaled for a single 18650PF cell. These choices are dictated by the fact that measurements on the same battery and the same vehicle are performed and made available by Dr. Phillip Kollmeyer at the Wisconsin-Madison University [40, 41]. All testing was performed in a thermal chamber, the characteristics of which are presented in [42, 43].

Measurements correspond to a random mix of five driving cycles: UDDS, LA92, US06, HWFET, and neural network. This makes it possible to simulate real driving cycles. The drive cycle tests are terminated when the voltage reaches 2.5 V. During the experiment, the following are measured:

- The measured voltage at the terminal of the battery cell in (V). The sense leads are welded directly into battery terminals.
- The measured current applied to the battery cell in (A).
- The time of the test measured in (s), which starts at zero at the beginning of each data set.
- The ambient temperature of the test chamber (where the battery cell is located) in degrees Celsius, which is maintained at 25 °C during the experiment.

These data will be used to identify the internal parameters of the battery cell.

#### 4. IDENTIFICATION PROCEDURE OF BATTERY CELL PARAMETER

In this article, we adopt the second-order Thevenin model with six parameters to be identified as shown in Figure 3. For the adjustment of these parameters, we used a set of experiences on the battery cell during different driving cycles, and we applied the least-squares nonlinear algorithm using MATLAB's parameter estimation toolbox. The estimation process of the parameters of the battery cell model is shown in Figure 5.

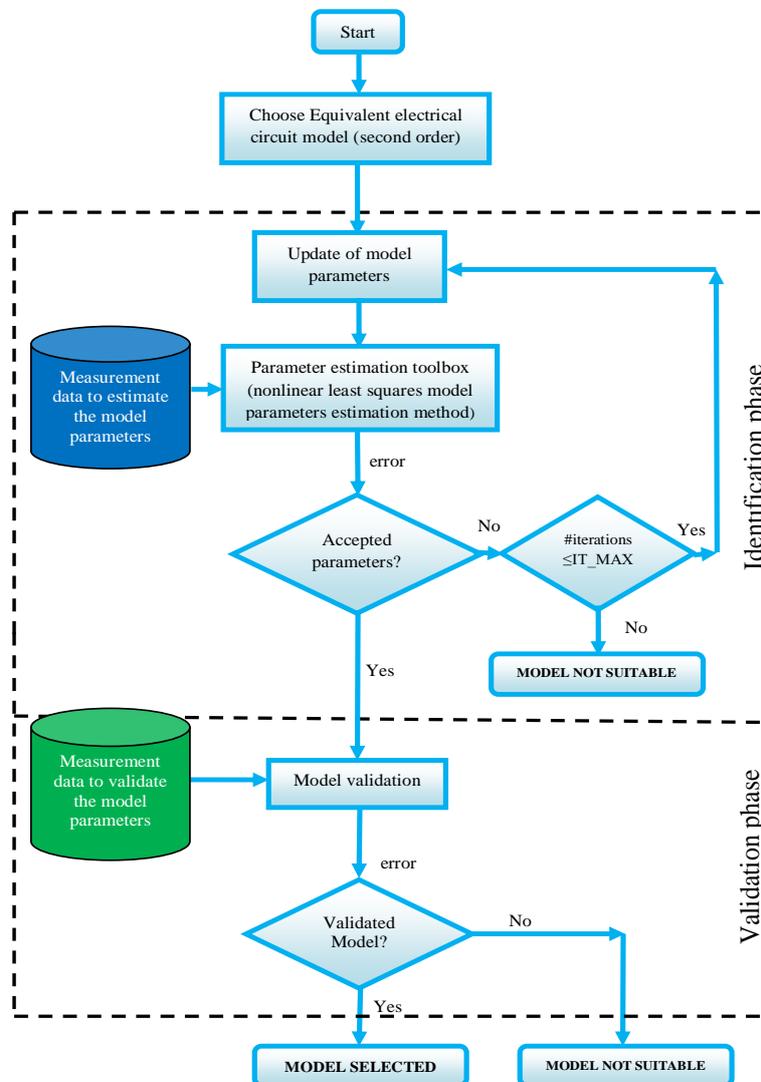


Figure 5. Flowchart of the estimation of battery cell model parameters

The estimation process of the parameters of the battery cell model is consists of seven steps:

- Step 1: Acquire experimental data sampled from the actual battery cell during a driving cycle of an electric vehicle to estimate the model parameter. For this step, we used data from experimental tests performed by Kollmeyer [40].
- Step 2: Select and build a battery cell equivalent circuit model (second-order) created in Simscape language integrated with the MATLAB/Simulink environment.
- Step 3: Specify the experimental data in MATLAB toolbox "Parameter Estimation" and simulate the model with the current profile used for parameter estimation and the initial intuitive parameters.
- Step 4: Select the model parameters and set the maximum value and the minimum value of each parameter to reduce the estimation time.
- Step 5: Specify optimization options using nonlinear least squares as an optimization method and the Levenberg-Marquardt or Trust-Region-Reflective as an optimization algorithm (A).
- Step 6: Specify the sum squared error as cost function (a function that estimation methods minimize) and initiate the parameter estimation process. If the error is not small enough to the tolerance value and the number of iterations is less than or equal to the maximum allowed value IT\_MAX, update the model parameters and move to the next iteration. Otherwise, the battery cell model is not suitable.
- Step 7: Validate the identified model with the estimated parameter by comparing the model response with the measured response of the battery cell. To validate the estimated model, it is necessary to use a data set different from that used to estimate the model parameters. For this step, we used data from other experimental tests available in [41]. If the error is not acceptable, the battery cell model is not suitable.

## 5. RESULTS AND DISCUSSION

### 5.1. Model identification

For the identification of the parameters of the battery cell model, namely  $U_{oc}$ ,  $R_0$ ,  $R_1$ ,  $R_2$ ,  $C_1$ , and  $C_2$ , we used the MATLAB toolbox "Parameter Estimation". The first step defines the experimental data: the desired input (the current profile during the driving cycle process ( $I_b$ )) and the desired output (the battery voltage across terminals during the driving cycle process  $U_b$ ) as a function of time in an Excel file (matrix of two columns).

For this step, we used the measurements performed by Kollmeyer [40]. Thereafter, we intuitively introduced the initial values of the parameters to be identified:  $U_{oc}$ ,  $R_0$ ,  $R_1$ ,  $R_2$ ,  $C_1$ , and  $C_2$ . Then we set the minimum value and the maximum value of each parameter to limit the parameter search interval and to reduce the identification time. Once the chosen estimation algorithm finishes its execution, it provides the new values of the model parameters.

The results of nonlinear least squares method for the Trust-Region-Reflective and the Levenberg-Marquardt algorithms are given in Table 1. We note that the Levenberg-Marquardt algorithm gives a mean square error (MSE) of 0.0013 in 3 iterations when Trust-Region-Reflective algorithm requires 8 iterations to estimate the model parameters for the same mean square error.

Table 1. Results of estimation algorithms

Algorithm	Levenberg-Marquardt	Trust-Region-Reflective
MSE	0.0013	0.0013
Number of iterations	3	8

In this work, we choose to present the results given by the estimated model using the Levenberg-Marquardt algorithm, which offers better results in terms of number of iterations compared to the Trust-Region-Reflective algorithm. The current variation and the terminals' voltage variation of the battery cell are obtained by lithium-ion cell tests during the driving cycle process of an electric vehicle until the battery cell is discharged. Figure 6 presents simulated and measured data. The two responses are different at the beginning of the simulation, which is normal because the initial parameters are chosen intuitively, and these values change as the identification process progresses. The current profile resulting from this cycle [40] is shown in Figure 7.

Once the identification process is complete, responses become similar, as shown in Figure 8, which indicates that the parameters are well estimated and that this method of identification has taken into account the dynamics of the accumulator in the time domain. Figure 9 illustrates the error between simulated and measured responses.

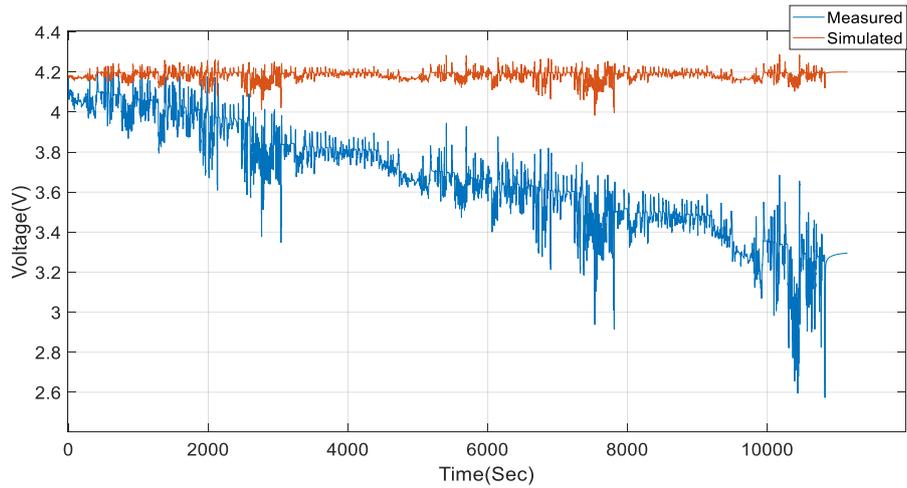


Figure 6. Initial measured and estimated response

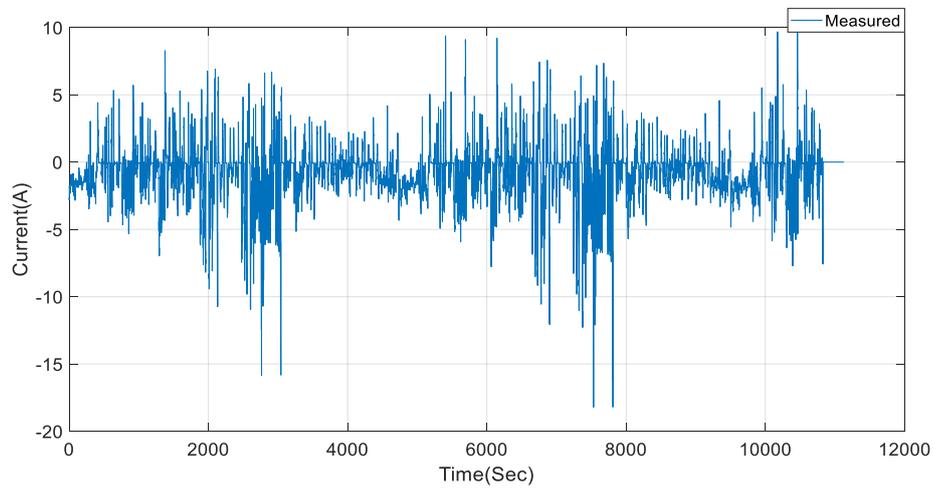


Figure 7. Current profile of driving cycle process

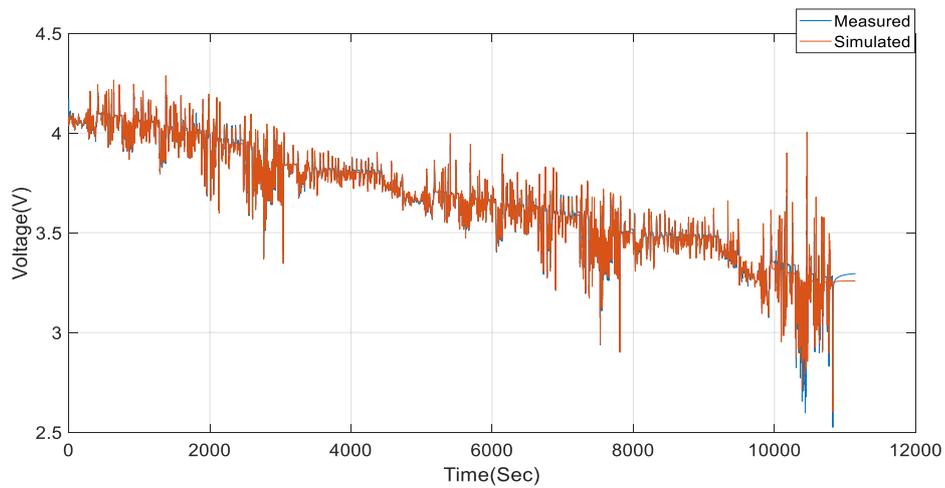


Figure 8. Voltage measured and voltage estimated during a driving cycle process

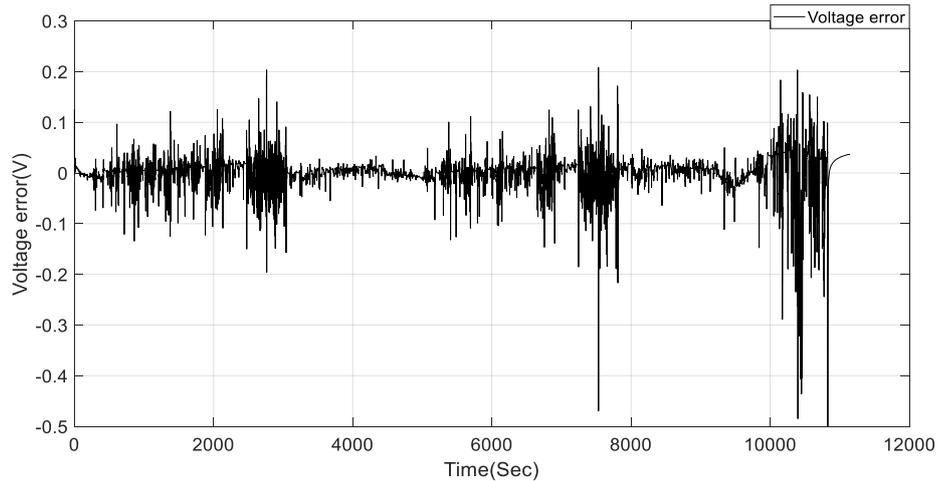


Figure 9. Voltage error between measured and estimated response

Figure 10 shows the variation of the internal parameters of the battery cell as a function of the state of charge SOC during the driving cycle process. This figure indicates that at interval between 100% and 30% of the SOC, the resistance values of R0 are around  $0.03 \Omega$  to simulate the voltage drop observed at the output of the battery cell. In the same zone, the capacitance values C1 and C2 vary to simulate the decay of the voltage, up to the last driving cycle process interval (interval between 30% and 0% of the SOC) where the values of the resistors R0, R1, and R2 change substantially to simulate the sudden voltage drop observed at the output of the battery cell.

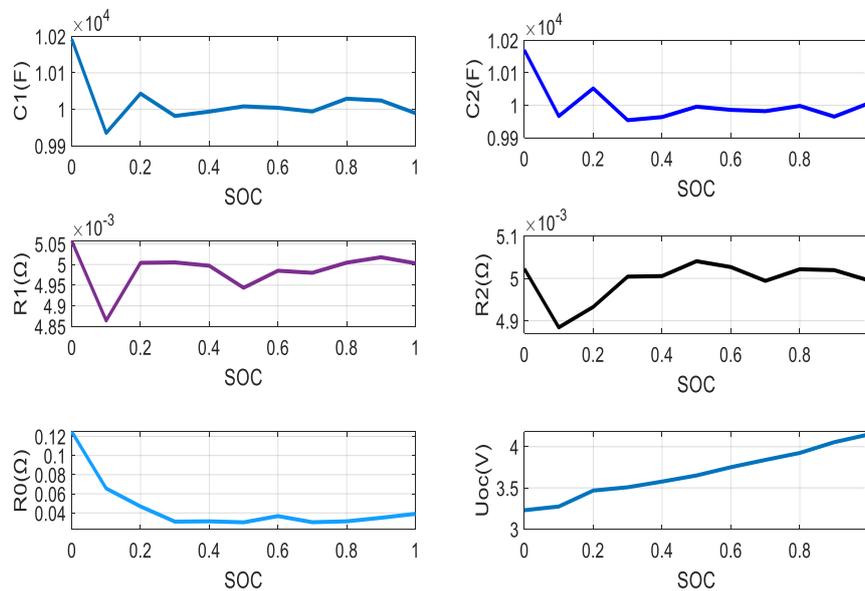


Figure 10. Evolution of the battery cell parameters according to the state of charge

**5.2. Model validation**

To validate the model based on its identified parameters, as illustrated previously see in Figure 3, and the algorithm used for identification (Levenberg-Marquardt), we used data that are different from those used in the model estimation phase. Our data consist of the driving cycles described in section 4: UDDS, LA-92, US06, NN, and HWFET. Table 2 presents the results obtained in terms of performance for the model identified based on mean squared error (MSE) criteria.

Table 2. The performance of the model in terms of MSE for the different driving cycles

DRIVE CYCLE TYPE	MSE
NN	0.001
LA-92	6.2674E-04
UDDS	3.8260E-04
US06	0.0023
HWFET	0.0016

All the cycles tested, as shown in Table 2, provide important results in terms of precision using MSE, especially when testing this model with the UDDS driving cycle, which gives interesting results: (MSE=3.8260e-04) and the LA-92 driving cycle (MSE=6.2674e-04). Hereafter, we only present the results of the UDDS driving cycles since they demonstrate better performance in term of MSE.

Figure 11 represents the current profile measured for the UDDS drive cycle, which is applied to our model to compare its response to that of MATLAB Simulink's battery, which is regarded as real (and not a simulation). Figure 12 presents the voltage measured during this driving cycle and the voltage estimated by our model. The error between the two responses is presented in Figure 13.

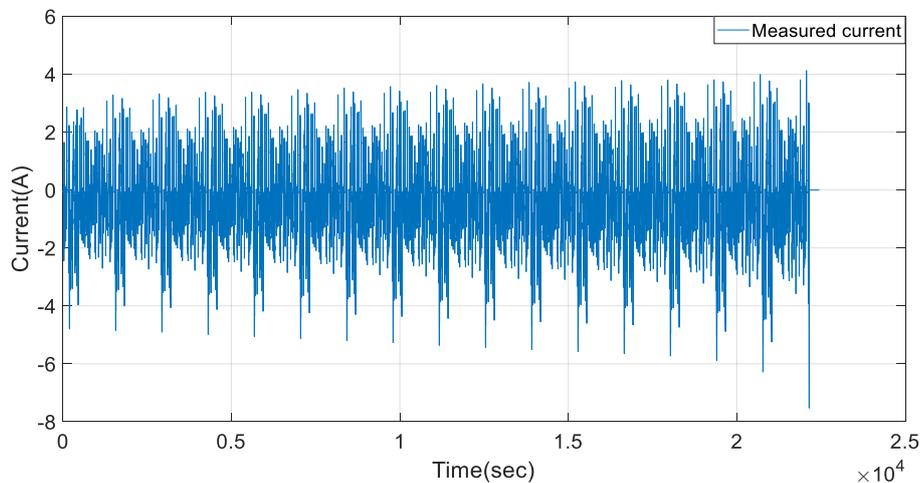


Figure 11. Current profile for UDDS drive cycle

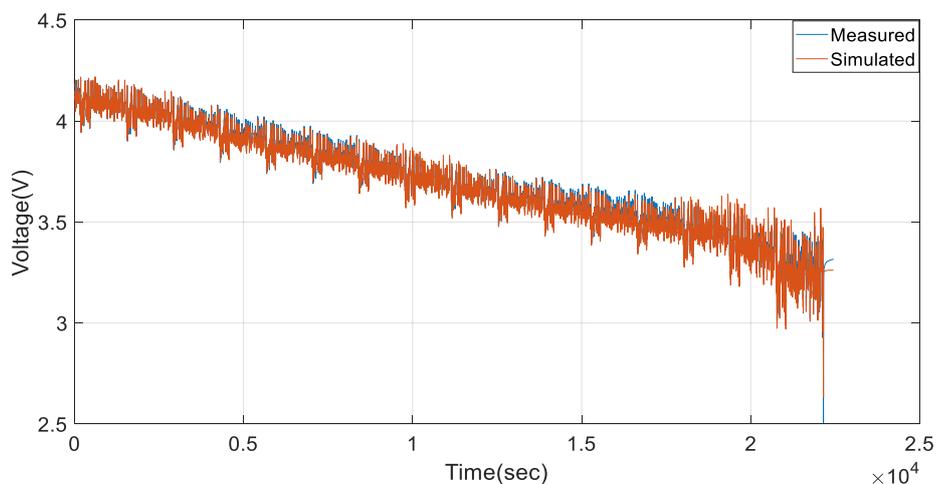


Figure 12. Voltage error between measured and estimated response for UDDS drive cycle

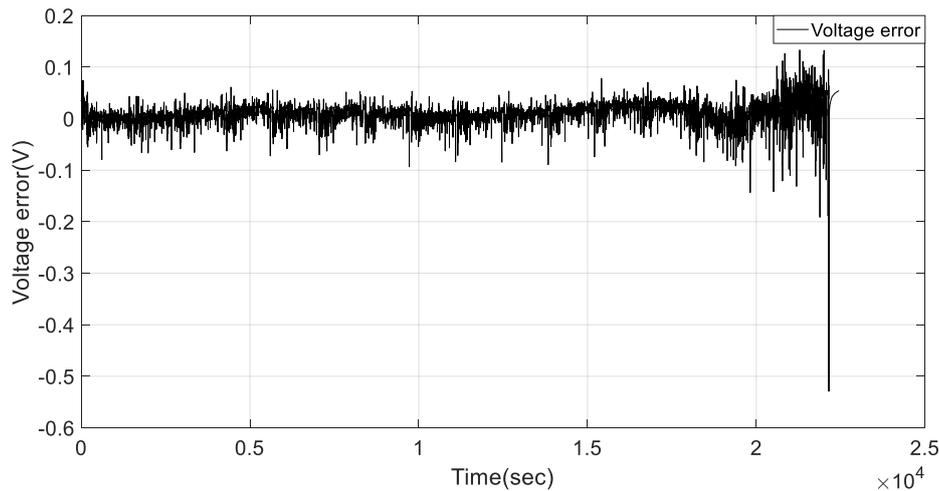


Figure 13. Voltage error between measured and estimated response for UDDS drive cycle

### 5.3. DISCUSSION

Through this work, we present a solution to predict the state of the battery cell used in different driving cycles of an electric vehicle; we have particularly focused our efforts on the prediction of the voltage. To validate the proposed model and the algorithm used to estimate its parameters during all phases of the use in electric vehicles, on the basis of the plotted objectives, model choice was made (a second order Thevenin model) and the adequate algorithm was selected (Levenberg-Marquardt). As a result, we were able to develop a model and estimate of its parameters. Moreover, to ensure the efficiency of the proposed model, a validation phase was established for different drive cycles that are described in section 4 (UDDS, LA-92, US06, NN and HWFET) and which represent different conditions and driving styles of an electric vehicle on highways and rural and urban roads.

From the results obtained in Table 2 and from Figure 11 to Figure 13, we note the correspondence between the simulation and experimental curves for the different drive cycles. This indicates that the adopted model and the associated method based on experimental data for parameter identification have made it possible to reproduce the actual behavior of our battery cell in an electric vehicle.

In addition, the mean square error was 0.0013 for the model estimation data,  $3.8260 \times 10^{-4}$  for validation data using UDDS drive cycle, and  $6.2674 \times 10^{-4}$  for validation data using LA-92 drive cycle. This demonstrates that the estimated model with identified parameters using the Levenberg-Marquardt algorithm successfully models the dynamic behavior of the battery cell during different driving cycles of an electric vehicle and interesting performance in terms of MSE. This is based on the results given in Table 2.

Furthermore, we can conclude that the Levenberg-Marquardt algorithm can estimate the parameters of the battery cell model in fewer iterations than with a Trust-Region-Reflective algorithm. This is based on the results presented in Table 1. The estimated model of the Levenberg-Marquardt algorithm makes it possible to successfully estimate battery cell behavior and is an excellent candidate for use in a battery management system in an electric vehicle.

### 6. CONCLUSION

Accurate battery simulation models are essential when analyzing and designing complex systems using this component in the electric vehicle. In this article, we proposed a model for a lithium-ion battery cell that takes into account the dynamic behavior of the battery cell in different conditions and driving styles of an electric vehicle on the highway and rural and urban roads. The model consists of a second order Thevenin model with six parameters. Experimentally measured data performed on an electric vehicle powered exclusively by a battery were used to estimate the parameters of the model. The model was validated using different driving cycles (UDDS, LA-92, US06, NN, and HWFET) based on MSE as model performance criteria. The step of model validation provided interesting results mostly for the UDDS drive cycle (MSE= $3.8260 \times 10^{-4}$ ) and for the LA-92 drive cycle (MSE= $6.2674 \times 10^{-4}$ ).

We used two different algorithms (Trust-Region-Reflective and Levenberg-Marquardt) with a nonlinear least squares method to estimate the battery cell parameters. The algorithms were compared to determine their suitability for the estimated battery cell voltage using the mean square error (MSE). The

Levenberg Marquardt algorithm gave the best parameter estimation results with the same MSE in fewer iterations compared to the Trust-Region-Reflective, which requires more iterations to estimate the parameters of the battery cell model.

In conclusion, for an integrated battery management system in an electric vehicle, the best choice is the model using the Levenberg Marquardt algorithm, as it requires fewer iterations than the other model algorithm does. Moreover, it offers an interesting result for different drive cycles of an electric vehicle (UDDS, LA-92, US06, NN, and HWFET), which represents different conditions and driving styles of an electric vehicle on the highway and rural and urban roads.

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## BIOGRAPHIES OF AUTHORS



**Jaouad Khalfi** is a Ph.D student at the Faculty of Sciences and Technologies, Cadi Ayyad University, Marrakech, Morocco. He received his Engineering degree in Electronics, Electrotechnics and Automation from the Faculty of Sciences and Technologies of Tangier (FSTT), Morocco in 2011. Since 2015, he has been a Teacher at the Moroccan Ministry of National Education, Vocational Training, Higher Education and Scientific Research. His research interests include battery management system (BMS) and Battery modeling.



**Najib Boumaaz** is an Assistant-Professor of Electronics at the Ecole Supérieure de Technologie of Safi, Cadi Ayyad University, Morocco, and a member of the Laboratory of Electrical Systems, Energy Efficiency and Telecommunications in the same University. He received his bachelor's degree in Electronics from the Normal School for Technical Education in Mohammedia (ENSET), Morocco, and his M.S from the University Cadi Ayyad of Marrakech, Morocco. Also he received his Ph.D in Electronic from the Polytechnic School of Nantes University, France. His research interests include electronics, telecommunications, statistical signal processing, random sampling and spectrum sensing.



**Abdallah Soulmani** is a Professor of Electronics and Industrial Computing at the Ecole Supérieure de Technologie of Safi, Cadi Ayyad University, Morocco, and a member of the Laboratory of Electrical Systems, Energy Efficiency and Telecommunications in the same University. He received his engineering degree in Electronics and Industrial Computing from the Polytechnic School of Nantes University, France, in 1994, and his Ph.D in Electronics from the same University in 2003. His research interests include software radio, random sampling, spectrum sensing, microelectronics and renewable energies.



**El Mehdi Laadissi** is an Associated Professor at the National School of Applied Sciences, Chouaib Doukkali University, El Jadida, Morocco, and a member of the Laboratory of Engineering Sciences for Energy (LabSIPE). He received his Master degree and his Ph.D in Electrical Engineering from the Normal School for Technical Education in Rabat (ENSET), Mohammed V University, Rabat, Morocco, respectively in 2014 and 2017. His research interests include renewable energies, battery management system (BMS) and Battery modeling.