Parameter Identification of an Electrical Battery Model using DC-IR Data

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Abstract: Parameter identification of an electrical battery model is significant for the analysis of the performance of a battery. In order to obtain an accurate electrical battery model, a series of cell characterization tests should be conducted which will take a considerable amount of time. In this study, in order to identify the parameters of the electrical battery model in a short amount of time with an acceptable accuracy, DC-IR data is used. DC-IR test will take less time compared to the cell characterization tests. For the parameter identification, one of the most commonly used evolutionary algorithm (EA), Genetic Algorithm (GA) is used for the curve fitting problem and its performance is compared with the Levenberg-Marquardt algorithm.

1 INTRODUCTION

The battery systems are having a bigger role in automotive industry since the emergence and development of Electrical Vehicles (EVs) and Hybrid Electrical Vehicles (HEVs). The performance metrics for batteries become more important, as the demand for electrical vehicles continues and sustains a competition on higher efficiencies, lower consumptions in an environment of stricter emission standards.

In automotive applications it is a necessity to estimate and control State of Charge (SOC), capacity, State of Health (SOH), remaining useful life, remaining available power of a battery since the performance of the vehicle is highly dependent on those battery states. Modern Battery Management Systems (BMS) use various methods to estimate these battery states in order to make sure that battery is working in a safe operating region. One of the methods that helps estimating the states of the battery and analyzing the battery performance is to obtain an accurate battery model. In this study, battery model for lithium-ion batteries are considered.

In literature, there are methods based on equivalent circuit model for the battery modeling, such as; electrochemical and electrical models (Waag et al., 2014). Electrochemical models define the chemical processes in a battery and are highly accurate models. However, they possess a high computational burden (Seaman et al., 2014). One of the most widely used methods among the electrical models is the Electrochemical Impedance Spectroscopy (EIS), but its complexity of the equipment and process are preventing the applications of EIS on to vehicles. EIS can estimate many properties of a battery; Resistance (ohmic, polarization), Capacitance (double-layer, coating), Constant-Phase Elements and Inductance, with an equivalent circuit approximation. But this method requires relevantly high precision equipment and AC-stimulation of the battery (Khan et al., 2016).

In this study, in order to benefit the advantage of using electrical equations, an electric equivalent circuit model is used. In literature, there are various studies that estimates the parameters of electrical equivalent circuit models (Sepasi et al., 2014), (Nejad et al., 2016), and (Mesbahi et al., 2016). In (Sepasi et al., 2014), a novel approach, model adaptive extended Kalman filter (MAEKF), is proposed in order to estimate the SOC of a lithium-ion battery. The SOC is not a measurable value, so it has to be estimated. An electrical battery model is used for this estimation and the parameters of the electrical model are identified by using an optimization algorithm in the proposed MAEKF method. The performance of the proposed approach is compared with the extended Kalman filter (EKF). The drawback of the EKF method is that it relies on the electric model parameters and may not handle the aging of the cell, accurately. The obtained results show that the proposed approach is able to handle this drawback of the EKF method. In (Nejad et al., 2016), the most

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commonly used lumped-parameter equivalent circuit models used in literature for modeling lithium-ion batteries are examined. The model parameters and states of the battery model are estimated by using dual Extended Kalman Filter (dual-EKF) and its performance is verified through pulsed current test results and the New European Drive Cycle (NEDC) driving cycle profile over a temperature range between 5$\sim$45$^{\circ}C$. Two cell chemistries are tested, lithium iron phosphate ($LiFePO_4$) and lithium nickel-manganese-cobalt oxide ($LiNMC$). The simulation studies indicate that two RC model structure is the optimum lumped-parameter equivalent circuit model for the battery energy and management applications. In (Mesbahi et al., 2016), a 40Ah lithium-ion battery cell is modeled by a dynamic equivalent circuit model to be used in Electric Vehicle (EV) applications. A hybrid Particle Swarm-Nelder-Mead (PSO-NM) optimization algorithm is used in the identification of the model parameters of the battery model. The performance of the battery model is tested with a dynamic driving cycle and a constant current/constant voltage (CC/CV) charge profile. The obtained results show that the modeling error is below 0.5% within a different operating conditions.

This paper proposes a simplification on equivalent circuit approximation by the usage of DC-IR data values. DC-IR values are internal resistance values of the battery, which are dependent both on SOC and temperature. For the calculation of the internal resistance, two measured voltage and current values are needed. These tests can be conducted in a short amount of time. In this work, the aim is to obtain an acceptable battery model in a reasonable amount of time.

In this study, two methods are used for the estimation of the electrical battery model, Genetic Algorithm(GA) and Nonlinear Least Squares (Levenberg-Marquardt Algorithm) and their performances are compared.

Genetic Algorithm is one of the most commonly used Evolutionary Algorithms (EAs) that can be applied to both constrained and unconstrained optimization problems. It can be used in a wide variety of engineering problems, such as; image analysis, optimization, classification, and etc. (Sopov and Ivanov, 2014), (Kaabi and Jabeur, 2015), and (Gasanova et al., 2014). In (Sopov and Ivanov, 2014), an image analysis problem, age recognition, is investigated. In this work, genetic algorithm is used with a novelty search. The obtained results indicate that the computational cost of the proposed approach is high compared to traditional approaches. However, it can be implemented to the problems that do not have a prior information about the problem. In (Kaabi and Jabeur, 2015), a Multi-Compartment Vehicle Routing Problem with Time Windows (MCVRPTW) with profit is considered. This problem is handled via a hybrid approach, genetic algorithm with Iterated Local Search (ILS). The novelty of this work is that the problem is formulated considering the time windows and collected profit. The genetic algorithm is used to obtain a minimum traveling cost and this solution is solved via Iterated Local Search considering temporal, capacity, and profit constraints. In (Gasanova et al., 2014), text classification problem is handled. The size of the text classification is reduced based on hierarchical agglomerative clustering algorithm. Then, the weights of the clusters are optimized with cooperative coevolutionary genetic algorithm.

The performance of the genetic algorithm is compared with one of the most commonly used parameter identification method, Levenberg-Marquardt. There are several applications that uses Levenberg-Marquardt method for parameter identification (Talebitooti and Torabi, 2016), (Dkhichi et al., 2014), and (Khan et al., 2014). In (Talebitooti and Torabi, 2016), a semi-epirical tire is modeled with a hybrid identification method, genetic algorithm and Levenberg-Marquardt method. The advantage of the hybrid method is indicated with a comparison of existing methods in literature, Starting Values Optimization technique (SVO), IMMa Optimization Algorithm (IOA) in terms of accuracy and convergence rate. In (Dkhichi et al., 2014), a highly non-linear solar cell is modeled based on Levenberg-Marquardt (LM) method with simulated annealing (SA). The obtained results of the proposed approach (LMSA) are compared to the methods in literature and it is observed that the proposed approach has a higher accuracy as compared to the other methods in literature. In (Khan et al., 2014), the State of Charge (SOC) estimation of the battery is estimated online based on parameter identification methods of the battery model and a linear recursive Kalman filter. The parameters of the battery model is identified through a combination of modified genetic algorithm and modified Levenberg-Marquardt algorithm. The proposed estimation framework is online and the SOC is estimated with an acceptable accuracy.

This study is organized as follows; In section 2, the electrical battery model is presented. In section 3, the parameter identification methods that are used in this study are given. In section 4, the simulation studies and results are presented. In section 5, the obtained results are analyzed and the future work in this area is discussed.

2 MODEL BASED APPROACH

A commonly used approach for battery modeling is the model-based approach. In literature, there are basically two methods for the model-based approach; electrical and electrochemical models.

Electrochemical models are highly non-linear and it is hard to implement them in a real time application (Waag et al., 2014). In this study, due to the highly complex structure of the electrochemical models, an electrical model is used for the battery model.

2.1 Electrical Battery Model

Electrical model of the battery has the advantage of using the electrical equations (Waag et al., 2014). In Fig. 1, a general representation of an n_{th} order electrical model is given. Depending on the degree of the electrical model, the accuracy is improving; however, the implementation in real-time systems will be harder due to the increased number of parameters.

In this work, for simplicity and computational efficiency, a second-order *RC* electrical model is used as seen in Fig. 2. In this model, the fast and slow dynamics of the battery are given by R_{fast}, τ_{fast} and R_{slow}, τ_{slow}, respectively.

The output of the electrical model is given as in the following:

$$u_{cell} = u_{OCV} + u_{Ohmic} + u_{fast} + u_{slow} \tag{1}$$

where u_{OCV} is the open circuit voltage (OCV), u_{Ohmic} presents the ohmic losses from the R_{Ohmic} resistance. It indicates the pure resistive effect at high frequencies. u_{fast} indicates the losses due to the double-layer effects (Butler-Volmer) between the electrode and electrolyte of the battery. u_{slow} represents the mass transport (Warburg) effect in the battery cell due to diffusion (Jossen, 2006).

$$u_{cell} = u_{OCV} + I_{pack} * \Bigg(R_{Ohmic} + R_{fast} * \left(1 - e^{(-t/\tau_{fast})}\right) + R_{slow} * \left(1 - e^{(-t/\tau_{slow})}\right) \Bigg) \tag{2}$$

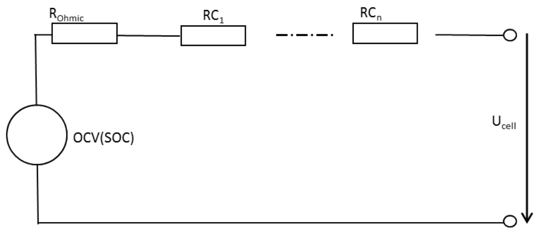

Figure 1: n_{th} order electrical equivalence circuit of a battery model.

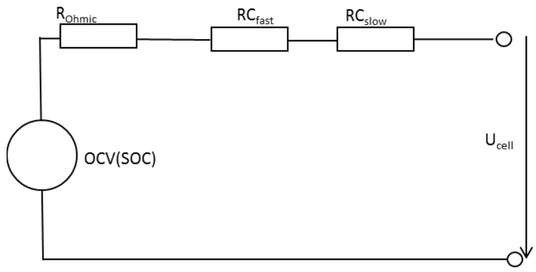

Figure 2: Second order electrical equivalence circuit of the battery model.

3 PARAMETER IDENTIFICATION OF AN ELECTRICAL BATTERY MODEL

In this work, the aim is to find the parameters of the electrical battery model based on DC-IR data. In order to obtain an accurate electrical battery model, cell characterization tests should be realized. However, these tests can be time consuming and they can last for weeks. In this time frame, the battery cannot be modeled and simulation studies, for instance, development of Battery Management System (BMS), estimation of the states of the battery, eg. State of Charge (SOC), remaining available power, etc., cannot be realized. In order to alleviate this problem, DC-IR test results can be used for the estimation of the parameters of the electrical battery model with an acceptable accuracy.

In literature, there are various methods for the internal resistance determination, (Ratnakumar et al., 2006) and (Ansen et al., 2013). In this study, a $42Ah$ lithium iron phosphate ($LiFePO_4$) type battery cell is studied. The DC-IR values are obtained by using the result of a pulse test. In this pulse test, the following *C*-rate charge and discharge pulses are applied: $C/5$, $C/3$, $1C$, and $2C$ for 10 seconds at 25°C. In order to stabilize the chemical reactions in the battery, the rest between two consecutive pulse is 10 minutes. The pulses are applied from 90% SOC until 10% SOC and SOC decreases 10%, incrementally. For each SOC decrement, the mentioned *C*-rate pulses are applied. From the last pulse until the pulse for SOC decrement, the rest is for 20 minutes. From the SOC decrement until the first pulse, the rest is for 10 minutes. The DC-IR values are obtained by measuring the charge and discharge voltage and current values by using the highest *C*-rate, $2C$, at 0.1, 1, 3, 6, and 10 time seconds. In Fig. 3, the voltage response of a 10 second $2C$ charge and discharge current pulse for 70%

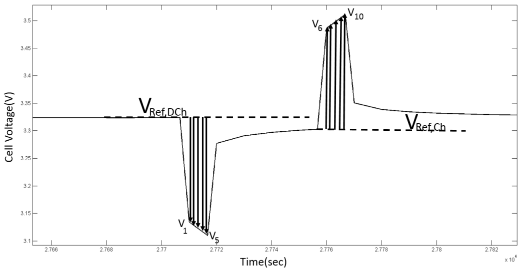

Figure 3: Voltage response of a 10 second 2C charge and discharge current pulse (at 70%SOC for 25°C).

Table 1: $R_{internal,Ch}(\Omega)$ values at 25°C and 70% SOC.

Pulse(sec)	$R_{internal,Ch}(\Omega)$
0.1	0.0002
1	0.0012
3	0.0021
6	0.0023
10	0.0025

SOC at 25°C is given as an example. The charge and discharge internal resistance values for 0.1 second is driven as follows:

$$R_{Internal,Ch,0.1s} = \frac{V_6 - V_{Ref,Ch}}{I_{Ref,Ch}} \tag{3}$$

$$R_{Internal,DCh,0.1s} = \left| \frac{V_{Ref,DCh} - V_1}{I_{Ref,DCh}} \right| \tag{4}$$

An example of the derived internal resistance values for charge current at 0.1, 1, 3, 6, and 10 seconds for 70% SOC at 25°C are given in Table 1.

Initially, it is considered that 1 *Ampere* is given to the electrical battery model described by Eq. 2. Thus, the output of the electrical battery model is the resistance values derived from the pulse test. In Fig. 4, the voltage response of the model is shown. As it is seen, the result at 0.1 second can be considered as the ohmic resistance, R_{Ohmic} of the electrical model. The unknown parameters of the electrical model are the time constants τ_{fast}, τ_{slow} and the gain values, R_{fast} and R_{slow}, of the fast and the slow dynamics of the electrical battery model, respectively. By applying a curve fitting approach, these unknown parameters of the electrical battery model can be estimated. The derived DC-IR values are used as the desired voltage values, which are used in the parameter identification methods described in the subsequent subsections.

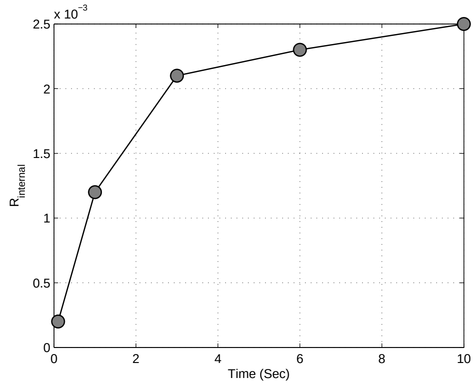

Figure 4: An example of the DC-IR data and curve fitting (For 2C charge current, for 70%SOC at 25°C).

3.1 Parameter Identification of Electrical Battery Model based on Genetic Algorithm

Genetic Algorithm (GA) is one of the Evolutionary Algorithms (EAs) that can be applied to a wide range of optimization problems. The fundamental ideas of Genetic Algorithm have been developed by John Holand in late 1960s and early 1970s. Genetic Algorithm is not a traditional optimization algorithm that uses gradient or Hessians. It uses probabilistic search method (Chong and Zak, 2001).

Genetic Algorithm is based on a biological process that uses natural selection. Every iteration, the parents are selected randomly from the current population and the offsprings of these parents are produced. This evolving procedure continues until the algorithm reaches the optimal solution.

In this work, genetic algorithm is used to find the parameters of the electrical battery model by using DC-IR data. DC-IR data set is composed of DC internal resistance values at different time seconds depending on the temperature and SOC values. The first iteration starts with an initial population which is composed of randomly generated individuals. Then, in the next iteration, the result of the current population is used. This iteration continues until the stopping criteria (ε), the change in the fitness function is below *1e-6* (ε <*1e-6*), is reached. The fitness function is the absolute value of the difference between the desired voltage value (DC-IR values) and the voltage value of the electrical battery model. It is given as in the following:

$$
\begin{aligned}
f_{fitness function} = & \left|u_{desired,R_{1sec}} - u_{fitted,R_{1sec}}\right| \\
& + \left|u_{desired,R_{3sec}} - u_{fitted,R_{3sec}}\right| \\
& + \left|u_{desired,R_{6sec}} - u_{fitted,R_{6sec}}\right| \\
& + \left|u_{desired,R_{10sec}} - u_{fitted,R_{10sec}}\right| \quad (5)
\end{aligned}
$$

The pseudo code of a general genetic algorithm is given in the following (Man et al., 1996):

function A general genetic algorithm()
{
  % Start with counter
    k = 0;
  % Randomly initialize the population
    Initialize Population: P(t)
  % Evaluate the fitness of the all
   initial individuals inside the population
    Evaluate: $f(P(t))$
  Get the best solution
  while (not terminate) (stopping criteria)
    % Increase the counter
      k = k + 1;
    % Select parents from
     the population for the offsprings
      Selection Parents: $P'(t)$
    % Create a combination of selected parents
      Combination: $P'_{new}(t)$
    % Mutate the offspring
      Mutate: $P'_{new}(t)$
    % Evaluate the offspring
      Evaluate: $f(P'_{new}(t))$
    % Select the best fits
      Population: BestFit($P(t)$, $P'_{new}(t)$)
}

3.2 Parameter Identification of Electrical Battery Model based on Nonlinear Least Squares Algorithm

In literature, Levenberg-Marquardt algorithm has been used for decades for non-linear fitting problems. It has been first introduced by Levenberg (Levenberg, 1944) and improved by Marquardt (Marquardt, 1963). Levenberg-Marquardt algorithm is one of the non-linear least squares algorithms and it is obtained by applying Levenberg-Marquardt modification to the Gauss-Newton method (Chong and Zak, 2001). In this study, the aim is to minimize the following error:

$$
\begin{aligned}
e = & \left(u_{desired,R_{1sec}} - u_{fitted,R_{1sec}}\right) \\
& + \left(u_{desired,R_{3sec}} - u_{fitted,R_{3sec}}\right) \\
& + \left(u_{desired,R_{6sec}} - u_{fitted,R_{6sec}}\right) \\
& + \left(u_{desired,R_{10sec}} - u_{fitted,R_{10sec}}\right) \quad (6)
\end{aligned}
$$

The objective function is given as follows:

$$f_{objective} = \frac{1}{2}\sum_{k=1}^{N}(e_k(x))^2 \quad (7)$$

where

$$x^{(k+1)} = x^{(k)} - \left(J(x)^T J(x) + \mu_k I\right)^{-1} J(x)^T r(x) \quad (8)$$

where $x = [\tau_{fast}, \tau_{slow}, R_{fast}, R_{slow}]^T$, $J(x)$ is the Jacobian matrix of e, I is the unity matrix, μ is the adjustment factor ($\mu > 0$), and $k = 1, \ldots, N$.

In this study, the performance of the genetic algorithm is compared with Levenberg-Marquardt algorithm.

4 THE SIMULATION STUDIES

Battery modeling is critical in order to analyze the performance and to estimate the states of a battery. In this study, DC-IR data is used to obtain the parameters of a second order electrical model of a LFP type battery.

The DC-IR data set is composed of DC internal resistance values at different time seconds depending on the temperature and SOC values. The data is obtained at 25°C considering different SOC values (between 10% and 90% with 10% increment). In DC-IR data, the pulse that corresponds to the smallest pulse time can be selected as the R_{Ohmic}, ohmic resistance of the battery model. Thus, the number of the estimated parameters are reduced to four instead of five. These parameters are the time constants and the resistance values of the fast and slow dynamics of the electrical battery model, τ_{fast}, τ_{slow}, R_{fast}, and R_{slow}, respectively. In addition, charge and discharge state of the battery is also taken into account for these parameters. These parameters are estimated by using

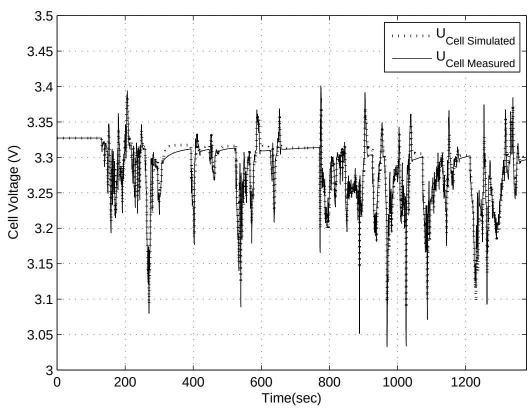

Figure 5: The comparison of the measured cell voltage with the simulation result via Genetic Algorithm.

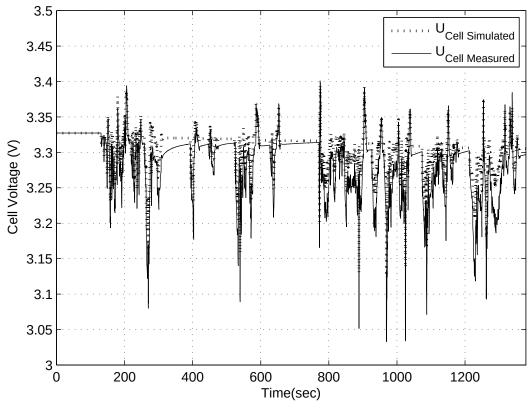

Figure 6: The comparison of the measured cell voltage with the simulation result via Levenberg Marquardt Algorithm.

two curve fitting methods, namely, Genetic Algorithm and Levenberg-Marquardt algorithm.

The obtained battery model is validated through a driving cycle at 25°C with an initial SOC value of ∼76%. The obtained results based on Genetic Algorithm and Levenberg-Marquardt algorithm are given in Figures 5 and 6, respectively. The obtained mean absolute error (MAE) values are given in Table 2. As it is observed, genetic algorithm has a less mean absolute error value and has a better convergence compared to the Levenberg-Marquardt algorithm.

Table 2: Comparison of Mean Absolute Error (MAE) values of the parameter identification methods.

MAE (V) (Genetic Algorithm (GA))	0.0081
MAE (V) (Levenberg Marquardt Algorithm)	0.0198

5 CONCLUSION

In this study, DC-IR data is obtained from a pulse test and it is used to obtain the parameters of an equivalent electric circuit of a LFP type lithium-ion battery. For this aim, two parameter identification algorithms are used, namely; genetic algorithm and Levenberg-Marquardt algorithm. The obtained results are verified through a driving cycle and the performances of the these two algorithms are compared in terms of mean absolute error (MAE) value.

The simulation studies indicate the utility of the genetic algorithm. The future work in this area will be to increase the order of the electrical battery model, eg., a third order battery model and to obtain a more accurate battery model.

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