19th IMEKO TC 4 Symposium and 17th IWADC Workshop
Advances in Instrumentation and Sensors Interoperability
July 18-19, 2013, Barcelona, Spain

Measurement technique for online EV battery state of life monitoring

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Abstract- An effective management of battery electric vehicles and implementation of vehicle-to-grid programs requires being able to monitor battery parameters to assess the state of the battery. Current techniques have reached good accuracy, but usually require long measurement procedures and powerful hardware that makes them unfit for online battery monitoring. In this paper a one-shot measurement technique and the first experimental results for battery parameter estimation are presented: it is fast and can be implemented on a low-cost microcontroller to realize online battery monitoring.
Keywords – *EVs, battery monitoring, online identification, V2G*

I. Introduction

The increase of oil prices, a developed awareness of public opinion and governments on the topics of renewable energy usage and reduction of pollutant gas emissions, the reduction of manufacturing costs, have led to an increasing interest towards Battery Electric Vehicles (BEVs) [1]. As such vehicles are and will become more popular, if not properly managed they will cause an unbearable load for the power grid: in order for the grid to sustain higher demand peaks, transmission and distribution lines should be sized up accordingly. In addition existing power plants should be enlarged or new ones should be built to support the newly determined demand. Moreover it is likely that the higher end of the power demand will be met with temporary generators (i.e. spinning reserves and quick-start ones, like pumped hydro or combustion turbines) which are the most expensive ones.
Nevertheless a massive adoption of BEVs can bring other significant advantages. The vehicles can be seen as dispatchable loads and thus they can be charged during off-peak periods; more than that, acting as a load, they can offer to the network some ancillary services such as regulation down and frequency regulation. Moreover, the energy stored in the batteries can be seen as a reserve of capacity for the network to be used to face sudden peaks. All these services go under the name of Vehicle-to-Grid (V2G) [2].

The continuous charge/discharge cycling that would result from the participation in V2G services tends to degrade the battery, reducing its useful life. It is thus important to determine a measure of the state of life of the batteries and a system that allows to predict when the battery will reach the end of its useful life (in the automotive field a battery is considered at the end of its life when the capacity reaches 80% of the original capacity) with current usage pattern [3],[4]. Such information can be used to determine both the adequate compensation for vehicle owners participating in V2G programs and the best management strategy for a fleet of BEVs. Therefore it is fundamental to monitor the parameters which are characteristic of battery operation.

Currently the state of art for measuring the value of the parameters characteristic of an electrochemical process is the Electrochemical Impedance Spectroscopy (EIS) [5],[6]. It can be successfully applied to batteries: to this end the cell is represented through an equivalent electric circuit [7],[8]. The method essentially consists of a perturbative characterization in which a small AC potential is applied to the electrochemical system and, from the nonlinear current response, is possible to determine the spectrum of equivalent impedance characteristic of the process. Using such information is possible to infer the values of the process parameters. Of course it represent a small signal characterization with consequent linearization of the system around the working point. Therefore is important, to the end of executing the measurements correctly, that the system is in steady state. For this reason executing a EIS characterization is a long process, especially considered that for each point a stimulus at a particular frequency must be provided and the corresponding current measured. Moreover it is also computationally heavy, thus not suitable for on-board battery monitoring. On this regard, executing one measure at a time it is difficult to guarantee that the battery is in steady state.

As seen the EIS measurement constitutes a slow process, not suitable for online-monitoring purposes. However having a fast method for determining the characteristic parameters of the process, which could be applied on the battery during its usage, is not only important to measure the wearing off of the battery life: appropriate monitoring techniques can be applied for the determination not only of the State of Health (SoH), but also of the State of Charge (SoC) of the battery. This would allow for more accurate forecasts regarding vehicle usage (i.e. available range, estimation of recharge time to attain a certain range, usage statistics, availability and consequent

compensation for V2G services) [9].
There exist a number of online estimation methods in literature [10]; mainly they can be divided into two categories: model based and non-model based. In the first case it is assumed a fixed model for the cell, and the variability of the parameters is intended as the perturbation of the model values. In this field Kalman filters and recursive system parameter estimation techniques have been found to be successfully applicable. To the second category belong techniques such as RVM or neural network, which basically look at the battery as a system whose laws and relations are not known, but create such laws themselves learning along with system usage [11].
This paper focuses on a measurement method to perform battery parameter identification that is fast and can be implemented on a low-cost microcontroller to realize online battery monitoring. It assumes a fixed model for the cell, which will be introduced in Section II. The implementation on a microcontroller embedded on the battery would allow for SoC estimation [10]. Moreover it may be used to implement the billing process and to make forecasts about the remaining battery life with the current usage pattern [12],[13].
The paper is organized as follows: in Section II the battery models which represent the state-of-art, and among which is the equivalent circuit model chosen for the implementation of the proposed method, will be briefly described; in Section III the proposed method will be introduced and Section IV will present the results obtained through simulations. Finally Section V will describe the first implementation of the measurement method on a ARM microcontroller.

II. Battery modeling

A rechargeable battery is composed of one or more electrochemical cells that convert stored chemical energy into electrical energy during a discharge process or convert electrical energy into chemical energy during a charge process [14]. Batteries are complex systems, and depending on the level of the detail required, they can be represented by several models.

Electrochemical models

Electrochemical models give a very detailed insight in the electrochemical processes that take place in the cell.
There exist several models which recur to physical laws and specific cell parameters to describe battery operation starting from the chemical reactions that happen in the cell. Generally these models involve coupled PDEs, therefore their solution results too computationally intensive to be implemented on devices embeddable on batteries and suitable for online monitoring purposes. Moreover they depend on very specific parameters characteristic of the individual cell: such parameters not only vary among different battery types, but also depend on the shape of the batteries, on the specific production lot, on the environment where the battery is being used (i.e. some of them depend on temperature). However, having sufficient computational power and knowledge of the intervening parameters, such models have a high degree of accuracy [15]. An example of electrochemical model is summarized in Table 1.

Table 1. Equations composing the electrochemical model for Li-Ion battery in [15]

Conservation of lithium in the solid phase $\frac{\partial c_s}{\partial t} = \frac{D_s}{r^2}\frac{\partial}{\partial r}\left(r^2 \frac{\partial c_s}{\partial r}\right)$	Where: - c_s *solid-phase lithium concentration* - c_e *electrolyte-phase lithium concentration* - ϕ_s *solid-phase potential* - ϕ_e *electrolyte-phase potential* - D_s *diffusion coefficient of Li/Li+ in the solid phase* - D_e *diffusion coefficient of Li/Li+ in the electrolyte phase* - ε_e *electrolyte volume fraction* - σ *electrode electronic conductivity* - κ *electrolyte ionic conductivity* - κ_D *electrolyte diffusional conductivity* - j^{Li} *reaction rate* - a_s *solid/electrolyte interfacial area per unit volume* - F *the Faraday constant* - R *the universal gas constant* - T *absolute temperature* - U *Open Circuit Voltage (OCV)*
Conservation of lithium in the electrolyte phase $\frac{\partial(\varepsilon_e c_e)}{\partial t} = \frac{\partial}{\partial x}\left(D_e \frac{\partial}{\partial r} c_e\right) + \frac{1-t_+^0}{F} j^{Li}$	
Conservation of charge in the solid phase $\frac{\partial}{\partial x}\left(\sigma \frac{\partial}{\partial x}\phi_s\right) - j^{Li} = 0$	
Conservation of charge in the electrolyte phase $\frac{\partial}{\partial x}\left(\kappa \frac{\partial}{\partial x}\phi_e\right) + \frac{\partial}{\partial x}\left(\kappa_D \frac{\partial \ln(c_e)}{\partial x}\right) + j^{Li} = 0$	
Butler-Volmer equation $j^{Li} = a_s i_o \left\{\exp\left[\frac{\alpha_a F}{RT}\eta\right] - \exp\left[-\frac{\alpha_c F}{RT}\eta\right]\right\}$	
Overpotential η *defined by* $\eta = \phi_s - \phi_e - U$	

For system level representation the deep insight on the electrochemical processes may not be needed, and simpler and faster models can be used, such as equivalent circuit models and mathematical models.

Equivalent circuit models

The equivalent circuit models resort to an analogy to electrical components, such as resistors and capacitors, to describe the V-I behavior of the cell. Two of the basic equivalent circuits are the simplified Randles cell and the Randles cell, which are reported in Fig. 1-2 [5],[6].

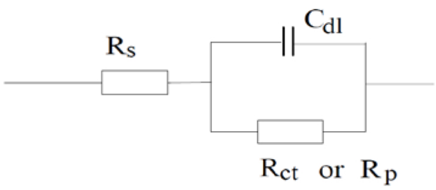

Figure 1. Simplified Randles cell

The Simplified Randles cell is one of most common cell models. It includes a solution resistance, a double layer capacitor and a charge transfer (or polarization resistance). The double layer capacitance is in parallel with the charge transfer resistance. In addition to being a useful model in its own right, the Simplified Randles Cell is the starting point for other more complex models.

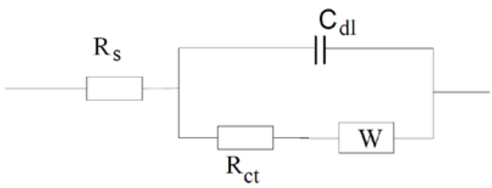

Figure 2. Randles cell

The equivalent circuit was initially proposed by Randles for modeling of interfacial electrochemical reactions in presence of semi-infinite linear diffusion of electro-active particles to flat electrodes. In this model, the impedance of a faradaic reaction consists of an active charge transfer resistance R_{ct} and a specific electrochemical element of diffusion W, which is also called Warburg element ($Z_W = A_W/(j\omega)^{0.5}$, where A_W is Warburg coefficient).

Depending on the degree of accuracy desired, it is possible to build a higher-order model starting from the Randles cell: in this case the higher attainable accuracy has to be balanced against the ease of implementation.
Equivalent circuit models are particularly suitable when the battery has to be studied as part of an electric circuit. However it must be highlighted that the parameter of the equivalent circuit tend to change with the operational conditions of the cell. In particular, considering the simplified Randles cell, the resistors' value tends to increase, while the capacitance decreases with the battery wearing off. Therefore recent studies make use of Randles cell (or the simplified version of it), updating the value of the parameters basing on the operational conditions of the cell. There are two approaches that can be followed here: the first one, very efficient especially in the case of onboard battery management systems, is to resort to Look-Up Tables that result from a previous characterization of the battery and state the values of the parameters corresponding to the parameters of influence [16]; another method is to derive a function able to express the variation of the resistors and capacitors in the model with the parameter of influence. Generally the considered parameter of interest are SOC, temperature and possibly current.

Mathematical models

Mathematical models describe the battery at a higher level of abstraction than either the electrochemical and equivalent circuit ones. In such models there is not the representation of the system as a whole, nor the insight of the specific physical and chemical processes taking place in the battery: they look at the battery through analytical relations that model its external behavior. Therefore they can make use of few equations and focus only on the battery properties of interest.
Mathematical models arise from the Peukert's law or the Shepherd equation [10], with additional terms empirically determined to improve the accuracy.
In this paper a simplified Randles cell model has been assumed as representative of battery behavior.

III. Proposed method

Representing the battery with a simplified Randles cell, a parametric identification algorithm is applied. As in the EIS, the cell is perturbed with a stimulus signal, that in this case is a current waveform. From the voltage response of the cell the parameters of the model, which describe the state of the cell, can be extracted.
Starting out with the measured voltage and current values, given the battery model, a model for the identification of the parameters must be chosen.
There exist several models for the identification of parameters; the one that has the best performances as system simulator is the Output Error (OE) model: however it is not linear with respect to the model characteristic parameters. That means that an iterative optimization method should be used to calculate model parameters. This makes the OE model less attractive for an online battery monitoring embedded device. Other identification

models, which allow a closed form calculation of the parameters are the AutoRegressive eXogenus (ARX). These two identification models are the ones implemented in the proposed method and will be introduced and described in detail in the following paragraphs.
For both models the stimulus electric current pattern is composed of a sum of sinusoidal waveforms, opportunely separated in frequency and with different phases. From the knowledge of the input and the response the spectrum of the transfer function, that in this case corresponds to the impedance, is obtained.
A least square algorithm is implemented to identify the values of the coefficients characteristic of the transfer function $\{a_0, \ldots, a_{nf+nb}\}$ that best fit the measured spectrum. Such coefficients are directly related to the values of the electrical components of the equivalent circuit. Additional detail on the measurement method may be found in [17].

Output Error (OE) model
If the *k-th* sample of the stimulus is represented by *x, c* represents the undisturbed output and the system output includes error *e* and is represented by *y*, the relation between them may be expressed as:

$$y(k) = c(k) + e(k) \qquad (1)$$

with

$$c(k) + a_0 c(k-1) + \cdots + a_{nf-1} c(k-nf) = a_{nf} x(k-nk) + \cdots + a_{nf+nb} x(k-nk-nb) \qquad (2)$$

The system is described by the equation

$$y(k) = G(z)x(k-nk) + H(z)e(k) \qquad (3)$$

where in the OE model $H(z) = 1$ is the error transfer function and $G(z)$ is the input transfer function, given by:

$$G(z) = \frac{a_{nf} + \cdots + a_{nf+nb} z^{-nb}}{1 + a_0 z^{-1} + \cdots + a_{nf-1} z^{-nf}} \qquad (4)$$

The optimization is carried out minimizing the one-step prediction error. Being non linear in the parameter of $G(z)$ an iterative method is required.
For a simplified Randles cell [5],[6], the transfer function is:

$$G(z) = \frac{a_1 + a_2 z^{-1}}{1 + a_0 z^{-1}} \qquad (5)$$

Considering the output vector of the identification function $\{a_0, a_1, a_2\}$, the values of the parameters are given by:

$$R_s = \frac{(a_1 - a_2)}{(1 - a_0)} \qquad R_p = 2\frac{[a_2 - a_0 a_1]}{(1 - a_0^2)} \qquad C = \frac{T(1 - a_0)^2}{4[a_2 - a_0 a_1]} \qquad (6)$$

with *T* the sampling period.

AutoRegressive eXogenous (ARX) moldel
The ARX model describes a relation between the input, error and output and most of the single input single output relationship is represented by this linear equation, which is given by,

$$A(z) * y(k) = B(z) * x(k) + e(k) \qquad (7)$$

where,

$$A(z) = 1 + a_0 z^{-1} + a_1 z^{-2} + \cdots + a_{nf-1} z^{-nf} \qquad (8)$$

$$B(z) = a_{nf} + a_{nf+1} z^{-1} + \cdots + a_{nf+nb} z^{-nb} \qquad (9)$$

x is the command signal, *y* is the output, *e* is the white noise. The error transfer function is $H(z) = 1/A(z)$ and the input transfer function is given by:

$$G(z) = \frac{B(z)}{A(z)} = \frac{a_{nf} + a_{nf+1} z^{-1} + \cdots + a_{nf+nb} z^{-nb}}{1 + a_0 z^{-1} + a_1 z^{-2} + \cdots + a_{nf-1} z^{-nf}} \qquad (10)$$

Given linearity of equation (7), it is possible to estimate the parameters in closed form calculation.
The form the $G(z)$ assumes is the same as in (5), and the determination of the parameters makes use of the same equations as in (6): the only difference with respect to the OE case relies in the optimization procedure and on the way the output of such procedure are presented.

ISBN-10: 84-616-5438-2 | ISBN-13: 978-84-616-5438-3

IV. Simulation results

The simulations have been carried out considering the cell represented by the equivalent circuit model, with characteristic parameters value deducted by existent works in literature. Both the case of a Ni-MH and Li-Ion battery have been considered. MATLAB and Simulink programming platforms have been used for the simulations. As stated in the previous Section, the current stimulus is composed of a sum of sine waveform at different frequencies and phases, so to excite all the frequencies of interest in the spectrum of the battery impedance transfer function. In Fig.3 e Fig.4 are reported an example of proposed technique for Ni-MH case.

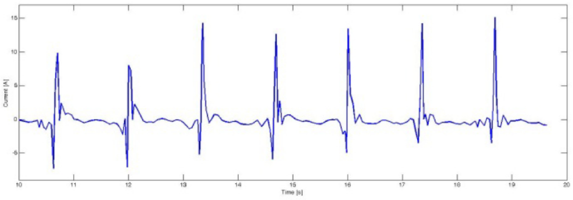

Figure 3. Current stimulus

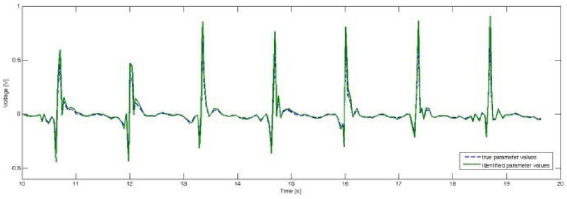

Figure 4. Voltage response with real and identified parameter values

The identification method has been tested against measurement noise: white noise has been added both on the stimulus and on the output of the battery model, to simulate measurement errors on both acquired channels.

Test on Ni-MH batteries

Simulations have been conducted on the model of Ni-MH battery using the following as value of characteristic parameters: Rs= 1 mΩ, Rp= 0.6378 Ω, C= 43.68 F. In Tables (2)-(3) are reported the results for noise amplitude up to 5%. The white noise has been added to each sample with amplitude calculated as a percentage (up to 5%) of the corresponding sample value.

As evidenced by the numerical results, starting with the same battery model, an identification realized through an OE model is more effective than with the ARX model. This behavior, however, is to be expected given the different nature (iterative compared to closed-form) of the optimization method. The identification using the ARX model is, on the other hand, much faster and therefore suitable for implementation on microcontroller. Moreover, for low noise figures, the results are comparable with the ones provided by OE method.

Table 2. Simulation results for Ni-MH battery with OE system model

OUTPUT ERROR MODEL						
Parameter\Noise	**0 %**	**0.2%**	**0.5%**	**1%**	**2%**	**5%**
Rs [mΩ]	1.000	1.000	0.999	0.999	0.999	0.997
Rs_error [%]	*6.8e-4*	*0.025*	*-0.099*	*-0.043*	*-0.072*	*-0.26*
Rp [Ω]	0.648	0.638	0.637	0.637	0.637	0.638
Rp_error [%]	*-1.1e-6*	*-0.003*	*-0.014*	*-0.032*	*-0.077*	*0.039*
C [F]	43.68	43.67	43.67	43.68	43.67	43.66
C_error [%]	*2.1e-6*	*-0.006*	*-0.023*	*0.019*	*-0.026*	*-0.033*

Table 3. Simulation results for Ni-MH battery with ARX system model

ARX MODEL						
Parameter\Noise	**0 %**	**0.2%**	**0.5%**	**1%**	**2%**	**5%**
Rs [mΩ]	1.000	0.999	0.998	0.999	0.981	0.8833
Rs_error [%]	*6.8e-4*	*-0.030*	*-0.23*	*-0.089*	*-1.9*	*-12*
Rp [Ω]	0.638	0.631	0.595	0.498	0.301	0.084
Rp_error [%]	*-1.1e-6*	*-1.1*	*-6.7*	*-22*	*-53*	*-87*
C [F]	43.68	43.67	43.64	43.50	43.22	40.93
C_error [%]	*2.1e-6*	*-0.009*	*-0.089*	*-0.40*	*-1.03*	*-6.3*

Test on Li-Ion batteries

Simulations have been conducted on the model of Li-Ion battery using the following as value of characteristic parameters: Rs= 24.22 mΩ, Rp= 7.36 mΩ, C= 458.1 F. In Tables (4)-(5) are reported the results for noise amplitude up to 5%. As it can be seen, the results are characterized by a much greater error than in the previous case, for both the OE and ARX identification method.

It is to be noted that the identification method was tuned on Ni-MH batteries: therefore the results emphasize the differences that exists between different battery technologies and underline the importance of particularizing an online identification method on the specific technology.

Table 4. Simulation results for Li-Ion battery with OE system model

OUTPUT ERROR MODEL						
Parameter\Noise	**0 %**	**0.2%**	**0.5%**	**1%**	**2%**	**5%**
Rs [mΩ]	24.220	24.221	24.217	16.631	13.776	10.064
Rs_error [%]	*2e-7*	*0.007*	*-0.011*	*-31*	*-43*	*-58*
Rp [mΩ]	7.359	7.358	7.363	7.691	1.054	1.423
Rp_error [%]	*-7e-7*	*-0.032*	*0.041*	*4.5*	*43*	*93*
C [F]	458.10	458.47	457.77	0.022	0.021	0.028
C_error [%]	*1.5e-6*	*0.081*	*-0.071*	*-99*	*-99*	*-99*

Table 5. Simulation results for Li-Ion battery with ARX system model

ARX MODEL						
Parameter\Noise	**0 %**	**0.2%**	**0.5%**	**1%**	**2%**	**5%**
Rs [mΩ]	24.220	24.180	23.986	23.275	20.840	12.518
Rs_error [%]	*2e-7*	*-0.16*	*-0.96*	*-3.9*	*-14*	*-48*
Rp [mΩ]	7.360	0.359	0.380	1.063	3.492	11.777
Rp_error [%]	*-7e-7*	*-95*	*-95*	*-85*	*-52*	*60*
C [F]	458.10	281.89	47.237	4.678	0.482	0.0774
C_error [%]	*1.4e-6*	*-38*	*-89*	*-98*	*-99.*	*-99*

ISBN-10: 84-616-5438-2 | ISBN-13: 978-84-616-5438-3

As seen from Fig.3 and Fig.4 and from Tables 2-5 the agreement between estimated and true quantities is enough for monitoring purposes in the case the technique is calibrated for the specific battery technology and the noise results not excessive.

V. Experimental results

The parameter identification algorithm was implemented on ARM microcontroller. In particular the ARX system model was considered, given its being less resource hungry. The execution time of the ARX model will be reported in the following. The calculation of the unknown parameters, with least squares method, depends directly on the multiplication of pseudo-inverse of a matrix by the output vector. The matrix was composed using samples from input and output signals. To evaluate the execution time, the authors took the data from the Matlab Simulink model and considered the implementation on the microcontroller only related to its calculation capabilities.

With this data the matrix was created and after some steps a pseudo-inverse was calculated. Two different sets of data was considered, 64 and 128 samples. The table 6 reports the execution time for two different microcontrollers. The data are for ARM Cortex_M3 (STM32F103RB) and ARM Cortex_M4 (STM32F407VG) microcontroller with a CPU system clock of 8 MHz. The microcontrollers are low cost, embeddable on the battery, and have sufficient processing power to execute the tasks at hand. Indeed, the results are very good in spite of the both microcontrollers not running at the maximum system clock frequency.

Table 6. Execution time of alghoritm on different microcontrollers

Exec time (ms)	64 samples	128 samples	256 samples
ARM – M3	18.76	36.36	63.57
ARM – M4	5.5	10.3	18.98

VI. Conclusions

In this paper a one-shot measurement technique has been implemented. Being it fast and not resource hungry, it can be implemented in a microcontroller embeddable in the battery for online monitoring purposes. The simulation results show that, although not being as precise as some offline methods like EIS, such technique can be used to monitor the State of Health. Moreover experimental results on the microcontrollers show the feasibility of the implementation on an embedded device. Future work will regard implementing the frontend to the battery, building a platform with adequate sensing capabilities.

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