Applied Energy 111 (2013) 416–427

Contents lists available at SciVerse ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Adaptive estimation of the electromotive force of the lithium-ion battery after current interruption for an accurate state-of-charge and capacity determination

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HIGHLIGHTS

- New adaptive approach for the EMF estimation.
- The EMF is estimated by observing the voltage change after the current interruption.
- The approach enables an accurate SoC and capacity determination.
- Real-time capable algorithm.

ARTICLE INFO

Article history:
Received 21 December 2012
Received in revised form 6 March 2013
Accepted 1 May 2013
Available online 4 June 2013

Keywords:
Battery monitoring
Electromotive force
State-of-charge determination
Capacity estimation

ABSTRACT

The online estimation of battery states and parameters is one of the challenging tasks when battery is used as a part of the pure electric or hybrid energy system. For the determination of the available energy stored in the battery, the knowledge of the present state-of-charge (SOC) and capacity of the battery is required. For SOC and capacity determination often the estimation of the battery electromotive force (EMF) is employed. The electromotive force can be measured as an open circuit voltage (OCV) of the battery when a significant time has elapsed since the current interruption. This time may take up to some hours for lithium-ion batteries and is needed to eliminate the influence of the diffusion overvoltages. This paper proposes a new approach to estimate the EMF by considering the OCV relaxation process within only some first minutes after the current interruption. The approach is based on an online fitting of an OCV relaxation model to the measured OCV relaxation curve. This model is based on an equivalent circuit consisting of a voltage source (represents the EMF) in series with the parallel connection of the resistance and a constant phase element (CPE). Based on this fitting the model parameters are determined and the EMF is estimated. The application of this method is exemplarily demonstrated for the state-of-charge and capacity estimation of the lithium-ion battery in an electrical vehicle. In the presented example the battery capacity is determined with the maximal inaccuracy of 2% using the EMF estimated at two different levels of state-of-charge. The real-time capability of the proposed algorithm is proven by its implementation on a low-cost 16-bit microcontroller (Infineon XC2287).

1. Introduction

The estimation of the battery electromotive force (EMF) at a present battery state is widely used in battery management systems (BMS) for the determination of state-of-charge (SOC) for various battery types [1–12]. Furthermore, the estimation of the change of the battery EMF between two different SOC is widely used for the determination of the battery capacity [4,13–19]. In both cases the relation between the EMF and the SOC of the battery is employed, which is exemplarily shown in Fig. 1 for the lithium-ion battery with nickel-manganese-cobalt-oxide (NMC) cathode and graphite anode material.[1]

When the battery gets charged or discharged and the current is interrupted subsequently, the battery enters the open circuit condition and the battery voltage (called open circuit voltage[2] (OCV))

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[1] A comprehensive review of other methods for the estimation of the battery SOC and capacity can be found, for example, in [27–30].

[2] Often the OCV is used as an equivalent to the EMF. In this work OCV is used to describe any measured battery voltage when the battery is under open circuit condition. The EMF is the battery OCV in equilibrium condition.

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http://dx.doi.org/10.1016/j.apenergy.2013.05.001

Nomenclature

ΔOCV	OCV change (V)
ΔSOC	SOC change (%)
A	parameter of the generalized impedance Z_{NUD} (–)
a	first parameter of the approximated error function (V/s^2)
a_x	first parameter of an empirical equation proposed in [10] (–)
b	second parameter of the approximated error function (V/s)
b_x	second parameter of an empirical equation proposed in [10] (s)
C	capacitance (F)
c	third parameter of the approximated error function (V)
C_a, C_b, C_c, C_d, C_e	capacitances of five RC elements that approximate the Z_{ARC} impedance (F)
C_{estim}	estimated battery capacity (Ah)
c_x	third parameter of an empirical equation proposed in [10] (V/K)
d_x	fourth parameter of an empirical equation proposed in [10] (V)
EMF kursive	estimated electromotive force (V)
F	amplitude of the error function (V)
$f()$	cost function (V^2)
$f_1(\psi), f_2(\psi), f_3(\psi), f_4(\psi), f_5(\psi), f_{10}(\psi)$	optimization functions (–)
$f_{\mathrm{err,\ fit}}$	error function approximated by a quadratic function (V)
f_{error}	error function (V)
$F_{\max}$	threshold for the amplitude of the error function (V)
func()	general functional dependency
i	index of the RC element (–)
N	number of the available sampled OCV values (–)
n	sample number (–)
N_0	number of the omitted samples of the error function (–)
$\mathrm{OCV}_{\mathrm{meas}}$	measured open circuit voltage (V)
$\mathrm{OCV}_{\mathrm{model}}$	modeled open circuit voltage (V)
R	resistance (Ω)
R_a, R_b, R_c, R_d, R_e	resistances of five RC elements that approximate the Z_{ARC} impedance (Ω)
R_{ser}	series resistance in impedance model (Ω)
t	time (s)
T	sampling period (s)
T_{bat}	battery temperature (K)
V	battery voltage (V)
V_{ZARC}	voltage on the Z_{ARC} element (V)
W_n	weighting factor (–)
Z_{ARC}	impedance of the parallel connection of the CPE element and resistance (Ω)
Z_{CPE}	impedance of the constant phase element (Ω)
Z_{NUD}	impedance of the non-uniform finite-length diffusion model (Ω)
Z_{RC}	impedance of the RC element (Ω)
$Z_{\mathrm{R\text{-}RC}}$	impedance of the R-RC model (Ω)
$Z_{\mathrm{R\text{-}ZARC}}$	impedance of the series connection Z_{ARC} and resistance R_{ser} (Ω)
Z_{UD}	impedance of the uniform finite-length diffusion model (Ω)
α	first parameter of the empirical OCV relaxation model proposed in [4,5] (–)
β	second parameter of the empirical OCV relaxation model proposed in [4,5] (–)
γ	third parameter of the empirical OCV relaxation model proposed in [4,5] (V)
τ	time constant (s)
ψ	depression parameter (–)
ω	angular frequency (rad/s)
Ω_{ZARC}	parameter of the Z_{ARC} element (s)

changes as schematically shown in Fig. 2. This process is often called OCV relaxation. After a significant time has elapsed since the current interruption, the change of the open circuit voltage is negligible small and the EMF can be measured as the OCV of the battery in its equilibrium condition (OCV = EMF).[3] The OCV relaxation process is mainly dominated by the diffusion processes and may take up to several hours especially when the battery is almost empty, at low temperatures and after charging or discharging with a high current rate.

In many applications the battery is charged or discharged continuously and therefore is under open circuit condition only for very short periods of time. These periods of time might be insufficient for OCV to relax completely, and as a result the accurate EMF measurement is not possible. The solution is the estimation of the EMF by observing the OCV relaxation process and predicting the relaxed OCV.

In [1] the EMF of a lead-acid battery is predicted by approximation of the OCV relaxation curve by two asymptotes if plotted on a semi-log scale: OCV = $f(\log(t))$. A set of parameters is employed to estimate the battery EMF considering these asymptotes. These parameters are found from previous laboratory experiments on a new battery. The disadvantage of the method is that when the battery ages, the used parameters describe the voltage relaxation process less and less accurate. The result is a decrease in accuracy of the EMF estimation.

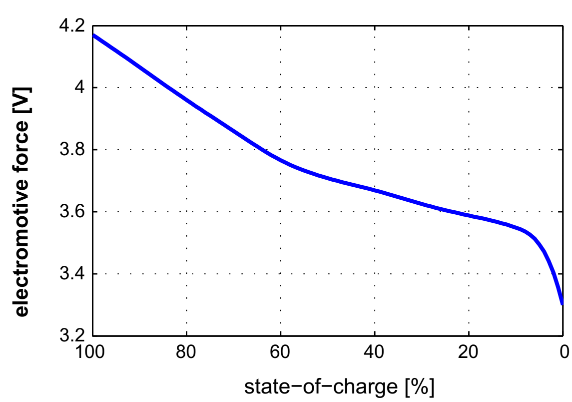

Fig. 1. The relation between the EMF and the SOC measured for a lithium-ion battery with NMC cathode and graphite anode material (cell of type SLPB100216216H manufactured by Kokam).

Another method is presented in [10]. It uses an empirical equation to predict the EMF by measuring the battery OCV, OCV slope (dV/dt) and the temperature: EMF = $a_x \cdot \mathrm{OCV} + b_x \cdot (\mathrm{d}V/\mathrm{d}t) - c_x \cdot T - d_x$. The parameters a_x, b_x, c_x and d_x have to be found by previous laboratory experiments. However, this method gradually reduces the accuracy of the estimation during the aging of the battery because the applied parameters become incorrect.

[3] In fact, the OCV of lithium-ion batteries depends additionally on the short time previous history: it is lower when the battery was previously discharged and higher when the battery was previously charged. This effect, called OCV hysteresis, is neglected in this work because it is very small for lithium-ion batteries with NMC cathode material. However, it can be considered simply employing, for example, two different curves for EMF-SOC relation shown in Fig. 1. For lithium-ion batteries with higher OCV hysteresis more complex hysteresis models might be required.