Battery open-circuit voltage estimation by a method of statistical analysis

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Abstract

The basic task of a battery management system (BMS) is the optimal utilization of the stored energy and minimization of degradation effects. It is critical for a BMS that the State-of-Charge (SoC) is accurately determined. Open-circuit voltage (OCV) is directly related to the State-of-Charge of the battery, accurate estimation of the OCV leads to an accurate estimate of the SoC. In this paper we describe a statistical method to predict the open-circuit voltage on the basis of voltage curves obtained by charging batteries with different currents. We employ a dimension reduction method (Karhunen-Loeve expansion) and linear regression. Results of our modelling approach are independently validated in a specially designed experiment.

1 Introduction

The last decade has seen an enormous growth in number of portable devices such as laptops and mobile phones. Development of such devices requires a drastic improvement in power supply and power management, and in particular, improvement in the capacity of rechargeable batteries. While the most significant progress in portable energy storage depends on the developments in chemical technology and material sciences, other areas such as charge regulation and battery monitoring can contribute significantly to the life-time performance of these batteries.

It is of most importance that the battery management system which controls charging and discharging of the battery, operates with an accurate estimate of the energy stored in the battery at any given time. The available fraction of the full capacity is called the State-of-Charge (SoC). An accurate estimation of the State-of-Charge is one of the main tasks of the BMS, Bergveld et al. [1], [2].

Several conventional approaches exist for determining the State-of-Charge. For Nickel-Metal Hydride (NiMH) batteries, one of these approaches is based on the measurements or estimation of electrical properties of the battery, such as its open-circuit voltage (OCV). By definition, the open-circuit voltage is the battery voltage under the equilibrium conditions, i.e. the voltage when no current is flowing in or out of the battery, and, hence no reactions occur inside the battery.

The open-circuit voltage is a function of State-of-Charge, $\mathrm{OCV} = f(\mathrm{SoC})$, and the function f is expected to remain the same during the life-time of the battery, i.e. it does not depend on the age of the battery. Note, however, that other battery characteristics do change with time, e.g. capacity is gradually decreasing as a function of the number of charge-discharge cycles. In this paper we only consider the problem of estimating the OCV. The question of how exactly the OCV depends on the SoC will be addressed elsewhere.

In this paper, we study the voltage of the battery, which is being charged with a constant current. Roughly speaking, with twice the current the battery is charged in half the time. Therefore, to compare the results of charging experiments with different currents, we study the battery voltage not as a function of time, but of the so-called Depth-of-Charge (DoC),

$$\mathrm{DoC}(t) = \frac{It}{Q_{\mathrm{nom}}},$$

where I is the charging current, t is the charging time and Q_{nom} is the nominal capacity. If one charges an empty battery, then, typically, in the first half of the charging period the State-of-Charge and the Depth-of-Charge coincide. Later, due to the presence of so-called side-reactions, the SoC increases slower than the DoC. Therefore, in the figures below the DoC can reach values larger than 100%, while SoC, by definition, does not exceed 100%.

The open-circuit voltage corresponds to equilibrium conditions. Therefore we estimate OCV as a limit of voltage curves corresponding to the decreasing sequence of currents. More specifically, using voltage curves obtained when various currents flow into the battery while it is being charged, we extrapolate to the current value equal to 0, hence obtaining the open-circuit voltage of the battery.

The second approach is based on a different limiting behavior. If a battery is left to "rest", then neglecting some physical processes such as self-discharge, we can assume that the battery voltage will stabilize to a certain value, which is the value of the open-circuit voltage at a given Depth-of-Charge. The relaxation period can take some time and the OCV is determined at the end of the resting period.

The first approach uses statistical methods to predict the OCV. The method maps a voltage curve to a small number of its Karhunen-Loeve (KL) coefficients; each curve becomes a point in a low-dimensional space and each point describes a voltage curve obtained for a specific current. A polynomial regression is then applied to model the dependence of the KL coefficient on the current. Extrapolating the regression model to zero current yields an estimate of the KL coefficient of the OCV curve.

The second approach is purely experimental. It requires a large number of partial charging experiments followed with substantial resting periods. This approach, however, is not very suitable for the application in battery management systems.

A good agreement between the results in OCV estimation by both methods is demonstrated.

All the experiments were performed with commercial AA size NiMH batteries of the type HHR110AAOK (Matsushita Battery Industries, Japan). The nominal battery capacity was about 1100 mAh at room temperature. The battery was placed on a special holder to ensure electrical connections. A precalibrated thermocouple is pasted on the battery to monitor the battery temperature. The set up was then placed in an ambient temperature controlled chamber. The battery voltage and temperature were measured during the experiment. Electrochemical measurements were performed using Maccor Systems (Maccor Inc, Tulsa, OK, USA Series 2300). Prior to all experiments, the battery was activated according to a standard activation procedure to ensure battery stability and hence increase reproducibility of the experiments and similarity between different used batteries. The activation procedure consisted of 5 cycles each containing the following steps: charging with 0.55A followed by a discharge phase containing a rest period of 1 h then discharging with -0.55A, a rest period of 15 min, further discharging with -0.11A and a final rest period of 15 min. The discharge steps have a battery voltage cut-off value of about 0.9V.

2 Open-circuit voltage estimation

2.1 Extrapolated OCV curve

Let us consider a group of voltage curves $V(t)$ obtained in an experiment when a NiMH battery was charged till 200% DoC with a given current value then completely discharged according to the discharge phase described in the activation regime and then charged again with a different current. The charging-discharging cycle was repeated for increasingly charging currents ranging from 0.011A to 2.2A.

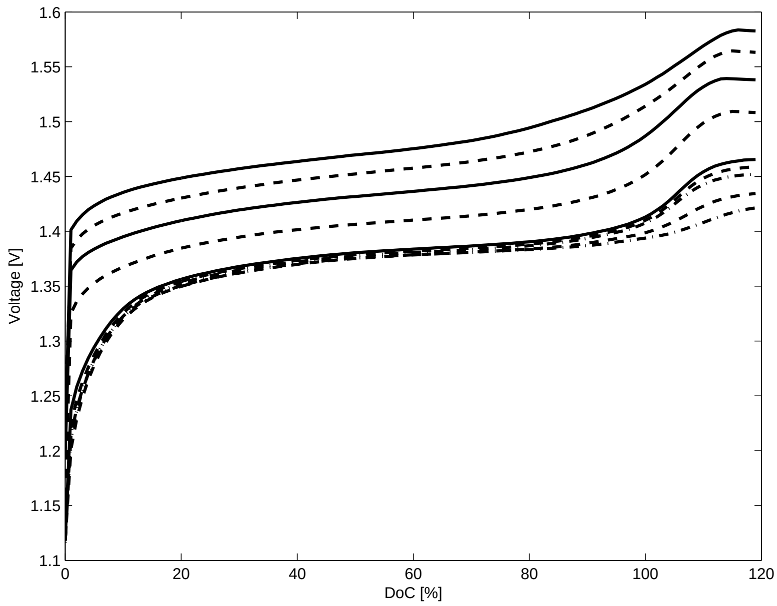

Figure 1: Voltage during charging with various currents: 0.011A, 0.022A, 0.055A, 0.077A, 0.11A, 0.55A, 1.1A, 1.65A, 2.2A (bottom-up).

Since the measurements were performed across many parameters, such as varying currents, voltages and time points, it is not possible to make a visual inspection of the relationship between these parameters in such a multi-dimensional matrix. One way to make sense of this data is to reduce its dimension. Several data decomposition techniques are available for this purpose: Karhunen-Loeve expansion (a form of principal components analysis, Flury [3], Jackson [4]) is one of such techniques.

Indeed, the representation given by the KL expansion with a limited number of KL coefficients is optimal in the mean-square sense. Such a dimensionality reduction has important benefits. First, noise is reduced, as the data not contained in the first coefficients is most probably due to noise. Secondly, in some cases, visualization becomes possible.

Let Y be an $n \times m$ matrix representing the battery voltage during charging with n different currents and sampled in m points in time. We assume that $n < m$. Figure 1 shows a typical experimental result.

The singular value decomposition (SVD) of matrix Y is given by

$$Y = V \Sigma U^T,$$

where V is an $n \times n$ unitary matrix, $\Sigma = \mathtt{diag}(\sigma_1, ...\sigma_n)$ is an $n \times n$ diagonal matrix, with $\sigma_1 \geq ... \geq \sigma_n \geq 0$, and U is an $m \times n$ matrix, whose columns are the first n columns of a unitary matrix. For $p \in [1, n]$, the Karhunen-Loeve rank p approximation Y_p of Y is:

$$Y_p = V_p \Sigma_p U_p^T,$$

where $\Sigma_p = \mathtt{diag}(\sigma_1, ...\sigma_p)$, V_p is an $n \times p$ matrix (first p columns of V), and U_p is an $m \times p$ matrix (first p columns of U).

Karhunen-Loeve approximation Y_p of Y can also be interpreted as follows. Denote by $\mathbf{y}_1, \ldots, \mathbf{y}_n \in \mathbb{R}^m$ the rows of Y. Suppose that we are looking for a linear subspace $W \subset \mathbb{R}^m$, $\dim(W) = p$, such that

$$\sum_{k=1}^{n} \left\| \mathbf{y}_k - \mathrm{P}_W(\mathbf{y}_k) \right\|^2$$

is minimal, where $\mathrm{P}_W(\mathbf{y})$ denotes the projection of vector $\mathbf{y}$ to W. Then the rows of U_p^T form the basis of the optimal subspace W, and the optimal projections are given by

$$\mathrm{P}_W(\mathbf{y}_k) = [\alpha_{k,1}, \ldots, \alpha_{k,p}]\ U_p^T, \quad k = 1, \ldots, n.$$

The matrix of Karhunen-Loeve coefficients $A = (\alpha_{k,j})_{k=1,j=1}^{n,p}$ satisfies $A = V_p \Sigma_p$.

In a practical application of the KL dimension reduction method, the choice of the parameter p depends on the importance of KL basis vectors for the description of the data, which is measured by the associated singular values, Karlis et al. [5]. Typically, for the data sets with some intrinsic smoothness, most of the original variability is captured by the first few basis functions. For our experimental data the first three Karhunen-Loeve coefficients seem to be sufficient: the heuristic indicators $\frac{\sigma_1+\sigma_2+\sigma_3}{\sigma_1+\ldots+\sigma_n} = 0.99$ and $\frac{\sigma_2+\sigma_3}{\sigma_2+\ldots+\sigma_n} = 0.83$ are appropriately large. Therefore, we put $p = 3$, see also Figure 2, showing the first 3 components.

If one wants to construct "experimental" voltage curves that have never been measured, under conditions that have never been used, one is forced to interpolate or extrapolate in the space of voltage curves, or, equivalently, in the space of KL coefficients. Therefore, one has to model the dependence of the KL coefficients on the parameters, influencing the experiment, e.g. current, temperature, age of the battery, etc. In our experiments, the value of the applied current is the only parameter that has been varied. Let $(\alpha_{k,1}, \alpha_{k,2}, \alpha_{k,3})$ be the KL coefficients describing the voltage curve obtained in the k-th experiment

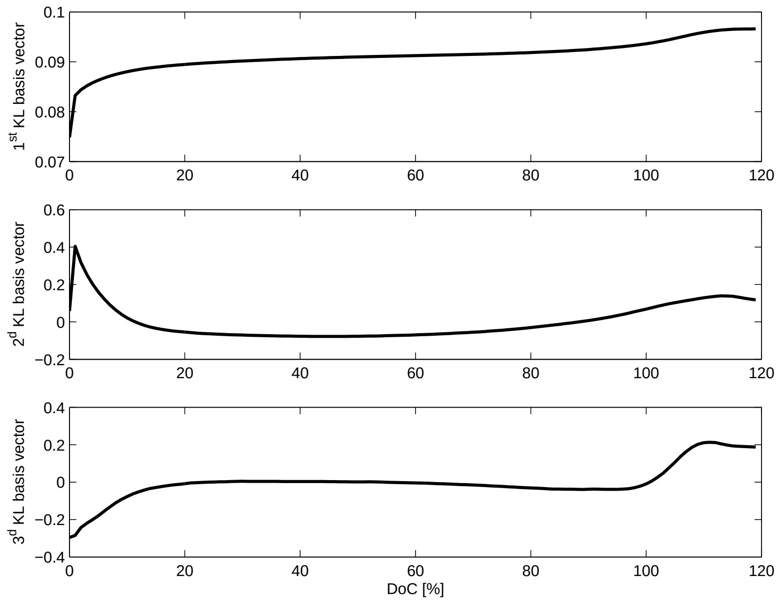

Figure 2: First three Karhunen-Loeve basis vectors.

when the current I_k was applied. Figure 3 shows the dependence of the first KL coefficient $\alpha_{k,1}$ on I_k. Figure 3 is quite interesting from the electrochemical point of view as well. There are clearly two different slopes in the dependence of $\alpha_{k,1}$ on I_k for low and high values of I_k, respectively. The presence of two different slopes is related to the fact that the reaction mechanism of oxygen evolution has two rate-determining steps, see Notten et al. [6].

In this paper we are primarily interested in the open-circuit voltage, i.e. zero current. Therefore we apply a linear regression model for the KL coefficients using only low currents 0.011-0.11A, i.e., the first 5 points in Figure 3. If one is interested in voltage curves corresponding to moderate currents (0.1-0.5A), kinetic equations derived in Notten et al. [6] provide a model for interpolation.

Since we adopted a linear model for the dependence of $(\alpha_{k,1}, \alpha_{k,2}, \alpha_{k,3})$ on I_k in low-current regime, we have to find only 6 regression parameters (a_1, b_1), (a_2, b_2) and (a_3, b_3), which are determined by

$$\sum_{k=1}^{K} |\alpha_{k,j} - (a_j + b_j I_k)|^2 \to \min, \quad j = 1, 2, 3,$$

where $K = 5$ is the number of low currents. Finally, setting current to 0 in the linear model, we obtain extrapolated values of the KL coefficients $\hat{\alpha}_1 = a_1$,

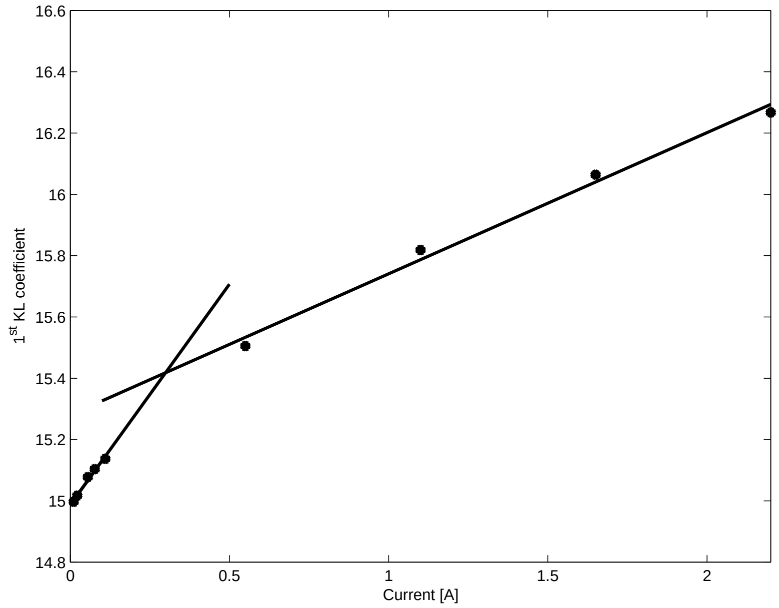

Figure 3: Dependence of Karhunen-Loeve coefficients on current value in low and high current regimes: dotted lines represent linear regression.

$\hat{\alpha}_2 = a_2$, $\hat{\alpha}_3 = a_3$, and the prediction for the OCV curve

$$\hat{V} = [\hat{\alpha}_1 \hat{\alpha}_2 \hat{\alpha}_3]\ U_3^T.$$

2.2 Experimental OCV curve

The values of the OCV for various values of the Depth-of-Charge can be measured in a separate experiment. Comparing these results with the results of our statistical approach we can independently validate our modelling assumptions.

In this experiment, the battery is charged with a constant current to a specific Depth-of-Charge, the current is then interrupted and the battery is allowed to rest for a certain period of time. The basic idea of that after current interruption, the battery reaches the equilibrium state (6 hours in our experiment) and hence the battery voltage is the value of the OCV at the given DoC. Figure 4 shows the voltage curves obtained in such experiments for 5 values of DoC. Figure 5 shows a good agreement between the results of our data analysis (solid line) and several experimentally observed values of OCV (dots).

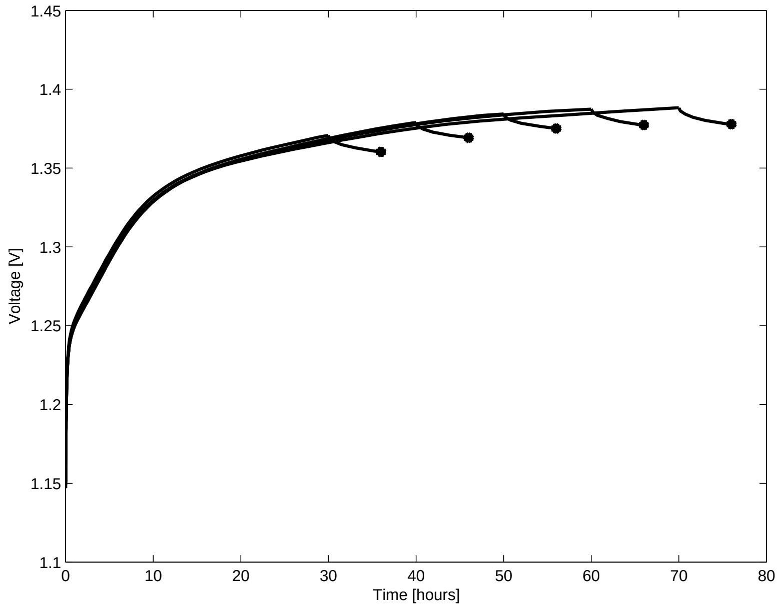

Figure 4: Partial charging experiment. Battery relaxation period is 6 hours, after which the OCV is sampled (dots). To ensure that the battery reaches equilibrium state in 6 hours, a very low current has been used for charging.

The experimental approach to the evaluation of the OCV is extremely time-consuming. Every point on the OCV curve is obtained by performing a separate charging experiment. On the other hand, the modelling approach allows a simultaneous estimation of the OCV for all values of the DoC based only on a few charging experiments with various currents. This aspect of our approach makes its application in adaptive battery management systems feasible.

3 Conclusion

In this paper we propose a method for determining the open-circuit voltage. Our approach is based on Karhunen-Loeve dimension reduction and modelling the dependence of the KL coefficients on physical parameters of the experiment. The method is also suitable for interpolation in the space of experimental voltage curves. Strikingly, results of our statistical analysis also detect an interesting electrochemical phenomenon recently observed for Ni-based rechargeable batteries. We also performed a series of independent experiments in which the OCV

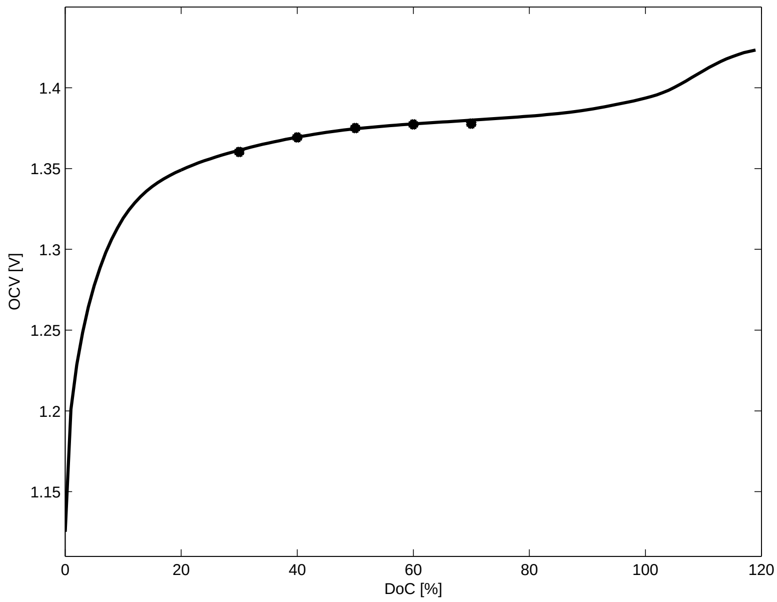

Figure 5: Open-circuit voltage as a function of DoC: extrapolated curve (solid line) and several experimental values (dots).

was evaluated directly for several values of the DoC. Results of both approaches are in a good agreement.

The method presented in this paper suggests a significant potential of the dimension reduction techniques in the development of battery management systems.

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