Comparison of Nonlinear Filtering Methods for Battery State of Charge Estimation

A Thesis

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# Abstract

In battery management systems, the State of Charge, obtained from voltage and current measurements, is a figure of merit. The estimation of State of Charge is challenging due to the nonlinear behavior of the battery, measurement noise, and the trade-off between accuracy and energy usage in selecting the sample rate. Additionally, for the purposes of eletrical-system design, an electrical-circuit battery model is useful, which presents additional filtering difficulties when compared to presently-used analytical models [wordy]. This thesis investigated the performance of various nonlinear filters for estimating the State of Charge using an electrical-circuit battery model.

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# Introduction

Batteries, particularly rechargeable ones, are used extensively in daily life. They provide the energy for such electrical systems as communication, automotive, and renewable power systems, among others. In order to design for and operate these systems, an accurate battery model and a means of simulating the model efficiently is needed. For example, modern battery charge and health management schemes use high-fidelity battery models to track the state of charge (SOC) and state of health (SOH); this information is then used to predict and optimize runtime of the battery. However, most batteries have nonlinear capacitive effects, which require the use of a nonlinear filter. This thesis provides one possible solution to this problem by choosing an appropriate battery model and testing the speed and accuracy of various nonlinear filters in determining the SOC.

## 1.1 Characteristics of Rechargeable Batteries

A high-fidelity battery model has to accurately reproduce the various characteristics of the battery. The characteristics included in most models are the capacity and the state of charge. More accurate models include nonlinear effects, such as the rate-capacity effect and the recovery effect, along with self-discharge and the effects of ambient temperature. The dynamic electrical attributes, such as the current-voltage (i-v) characteristics and transient responses, can also be modeled.

The capacity of a battery is the amount of electric charge it can store, measured in the SI unit

Ampere-hours (Ah). Commonly, for rechargeable battery specifications, the subunit milliampere-hour (mAh) is used. Due to the electrochemical nature of batteries, a battery's available capacity decreases as the rate of discharge increases. Therefore, the capacity for a battery is typically stated for a given discharge rate. For lead-acid batteries, this diminishing capacity with increasing discharge rate is known as Peukert's law, which states that for a one-ampere discharge rate [1]

$$C_p = I^k t, \tag{1.1}$$

where $C_p$ is the capacity at a one-ampere discharge rate in Ah, $I$ is the discharge current in A, $t$ is the time to discharge the battery in hours, and $k >= 1$ is the dimensionless Peukert constant, typically between 1.1 and 1.3 for a lead-acid battery. The constant $k$ only equals unity for an ideal accumulator, so for real batteries, $k$ is always greater than unity. Thus, for a given increase in the discharge current, the discharge time decreases by a proportionally greater amount. Therefore, the effective, or available, capacity $Ct$ is reduced. For a general battery, this effect is known as the rate-capacity effect. Related to this is the recovery effect, so called because when a battery is allowed to rest during an idle period, the battery "recovers" available capacity previously lost during discharge due to the rate-capacity effect.

Both the rate-capacity effect and the recovery effect can be explained by the electrochemical nature of the battery. During discharge the concentration of the active material around the electrode is depleted and the active materials in the depletion region move towards the electrode to reduce the concentration gradient [2]. Because the speed at which the concentration gradient is equalized is limited, the faster the rate of discharge, the less active material has been replenished, resulting in a decrease in the capacity. Likewise, when the battery is allowed to rest, the active material gradient has additional time to equalize and increase the available capacity.

Closely related to the capacity is the SOC. This thesis defines it as the ratio between the remaining capacity and the maximum capacity, with both capacities measured using the amount of active

material within the battery. This definition then denotes the proportion of remaining chemical energy rather the the available energy and is unaffected by the rate-capacity and recovery effects. Note that a fully charged battery has an SOC of unity and a fully discharged battery has an SOC of zero, regardless of the available capacity. Additionally, it is convenient to establish the relationship between the SOC of the battery and its open-circuit voltage $V_{OC}$, which is useful for simulation of the i-v characteristics and transient responses. $V_{OC}$ can be thought as the limit of the measured battery voltage after recovery.

Other more minor effects that are usually incorporated into models are self-discharge, the effect of ambient temperature, and aging. Self-discharge refers to an idle battery decreasing its SOC over time due to internal chemical reactions. It is dependent on the type of battery, SOC, ambient temperatures, and other factors. The ambient temperature has effects on the internal resistance of the battery and the self-discharge rate. Commonly, the battery is designed to operate with a narrow range of temperatures. Below the operating temperature range, the internal resistance increases, decreasing the capacity. Above the operating range, the internal resistance decreases, not only increasing the capacity but also the self-discharge rate; thus, the actual capacity is lowered due to the increased self-discharge. Aging refers to the decrease in battery performance measures, such as capacity, self-discharge, and internal resistance, over time due to unwanted chemical reactions. In practice, aging is indicated by the SOH, defined as the ratio between the current maximum capacity and that of a new battery. The SOH threshold at which the battery performance is considered too degraded varies by application.

## 1.2   Rechargeable Battery Models

This study is concerned with prediction of the SOC of a battery using noisy measurements of its current and voltage. To do so accurately for a general load, incorporation of the rate-capacity and recovery effects as well as the transient i-v characteristics is desirable. It is also desirable that the

model can be easily tuned for different battery types. There are several battery models that meet some or all of these requirements. The remainder of this section discusses the characteristics of these battery models and chooses the best one for the purposes of this thesis.

The battery models can be divided into five categories: electrochemical, computational intelligence, analytical, stochastic, and eletrical-circuit models. The first two types are very accurate but computationally expensive. Among the five types, electrochemical models are the most accurate, but they require in-depth knowledge of the chemical processes to create and impose large computaional costs [3]. Computational intelligence models can be similar in accuracy to electrochemical models, but their learning period is highly computationally expensive [4, 5]. The remaining categories and examples of battery models in them will be discussed in the remainder of this section.

Analytical models are simplified electrochemical models that trade off accuracy for simplicity. One of the simpliest such models is Peukert's law, described above. It is able to model the rate-capacity effect but not the recovery effect. More complicated models, such as the kinetic battery model and the diffusion model, are able to describe both the rate-capacity effect and the recovery effect. However, the current examples of analytical models cannot describe the transient i-v characteristics of batteries.

The kinetic battery model, initially created for large lead-acid batteries, describes the battery as a kinetic process, using two charge wells for the bound and available charges connected by a valve whose flow rate is proportional to the height difference between the wells [6]. The flow rate of the valve should be lower than the typical discharge rate of the battery. During discharge from the available-charge well, the bound charges flow through the valve to equalize the heights of the two wells. It can be seen that for slower discharge rates, more charge flows through the valve and the effective capacity increases. Likewise, during idle periods for the battery, the available charge increases. Thus, the model is able to describe the rate-capacity and recovery effects.

Related to the kinetic battery model is the diffusion model, which describes the movement

of the ions in the electrolyte of a lithium-ion battery [7]. Like in the kinetic battery model, the difference in the concentration of adjacent ions along the length of the battery determines the diffusion rate of the ions. The available charges are those ions directly touching the electrode of the battery. It can be seen that the kinetic battery model is a first-order approximation of the diffusion model [3], so naturally the diffusion model also describes the rate-capacity and recovery effects.

Stochastic models

Finally, eletrical-circuit models

## 1.3   Nonlinear Filtering Methods

The battery model chosen for the purposes of this thesis has the advantage that it can be written in state-space form for use with commonly available state space filters. The rest of this section discusses the various nonlinear filtering techniques that can be applied to the model. [I have yet to read the paper.]

## 1.4   Figures of Merit

# 2

# Methodology

As discussed in the previous section, this thesis considers the electrical-circuit model proposed by Chen and Rincón-Mora [8].

## 2.1 Battery Model

As discussed in the previous section, this thesis considers the electrical-circuit battery model shown in Figure 2.1. This thesis assumes that

For convenience, assume that the voltage $V_{SOC}$ measured in volts equals the SOC so that $V_{SOC} \in [0, 1]$ V. Notice that the model consists of two circuits that, while not independent, perform different functions. The one on the left with the current source tracks the SOC, which changes from charging and discharging of the battery as well as from self-discharge, while the one on the right with the voltage source models the transient i-v characteristics along with the open-circuit voltage $V_{OC}$.

For the left circuit, the capacitance $C_{\mathrm{cap}}$ can be calculated

Recall that $V_{OC}$ is a nonlinear function of the SOC. In addition, the other

The nonlinear parameters of the model for a typical lithium-ion battery are [need source]

$$R_s = 0.1562e^{-24.37V_{SOC}} + 0.07446 \qquad (2.1)$$

$$R_{ts} = 0.3208e^{-29.14V_{SOC}} + 0.04669 \tag{2.2}$$

$$C_{ts} = -752.9e^{-13.51V_{SOC}} + 703.6 \tag{2.3}$$

$$R_{tl} = 6.603e^{-155.2V_{SOC}} + 0.04984 \tag{2.4}$$

$$C_{tl} = -6056e^{-27.12V_{SOC}} + 4475 \tag{2.5}$$

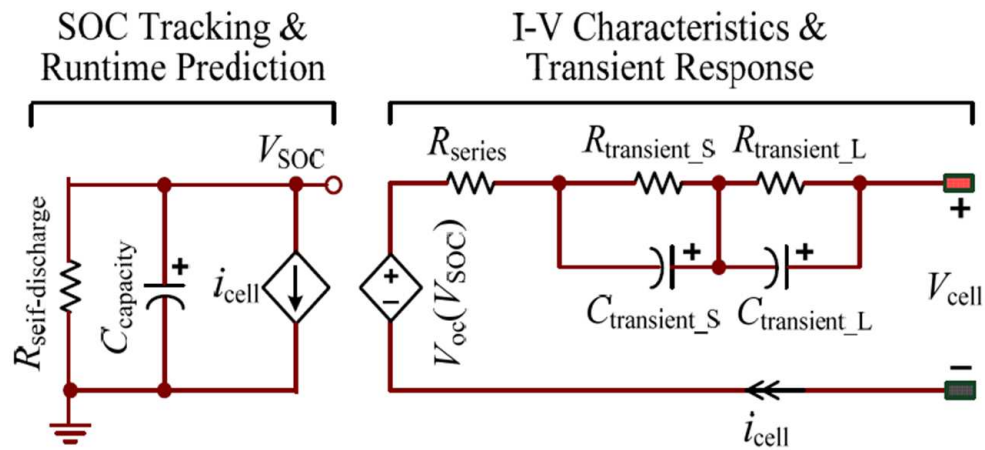$$V_{OC} = -1.031e^{-35V_{SOC}} + 3.685 + 0.2156V_{SOC} - 0.1178V_{SOC}^2 + 0.3201V_{SOC}^3 \tag{2.6}$$

The circuit on the left is a linear, time-invariant (LTI) system, which has the following state space model:

$$x = C_{cap}V_{SOC} \tag{2.7}$$

$$\dot{x} = \frac{x}{R_{sd}C_{cap}} - \frac{i_{cell}}{C_{cap}} \tag{2.8}$$

$$V_{SOC} = \frac{x}{C_{cap}} \tag{2.9}$$

The circuit on the right is a nonlinear system, since the coefficients are dependent on the voltage



**Figure 2.1.** Battery model for simulation. [This is taken from a paper, but I will probably redo it and change some labels, e.g. Rseries to Rs]

$V_{SOC}$. The corresponding state space model is [I think that I changed the model a little for my simulations by adding an output for $i_{\text{cell}}$. Also, the "nonlinear" simulations combine both ss systems using the given Voc nonlinearity].

$$x = \begin{bmatrix} v_{C_{ts}} & v_{C_{tl}} & V_{OC} \end{bmatrix} \tag{2.10}$$

$$\dot{x} = \begin{bmatrix} -1/R_{ts}C_{ts} & 0 & 0 \\ 0 & -1/R_{tl}C_{tl} & 0 \\ 0 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1/C_{ts} & 1/C_{tl} \end{bmatrix} i_{\text{cell}} \tag{2.11}$$

$$v_{\text{cell}} = \begin{bmatrix} -1 & -1 & 1 \end{bmatrix} x - R_s i_{\text{cell}} \tag{2.12}$$

The two electrical circuits and the nonlinear voltage source that connects them can be written as one state space system for use with nonlinear filters discussed in the first section, yielding

## 2.2 Filter Design

In order to determine the necessity of incorporating the nonlinear relationship between $V_{SOC}$ and $V_{OC}$ in the filter design, the linearized right-hand circuit with $V_{SOC} = 0.6$ V and the left-hand circuit were processed by a Kalman filter in each iteration and in that order, with the nonlinearity calculated implicitly.

## 2.3 Simulation Setup
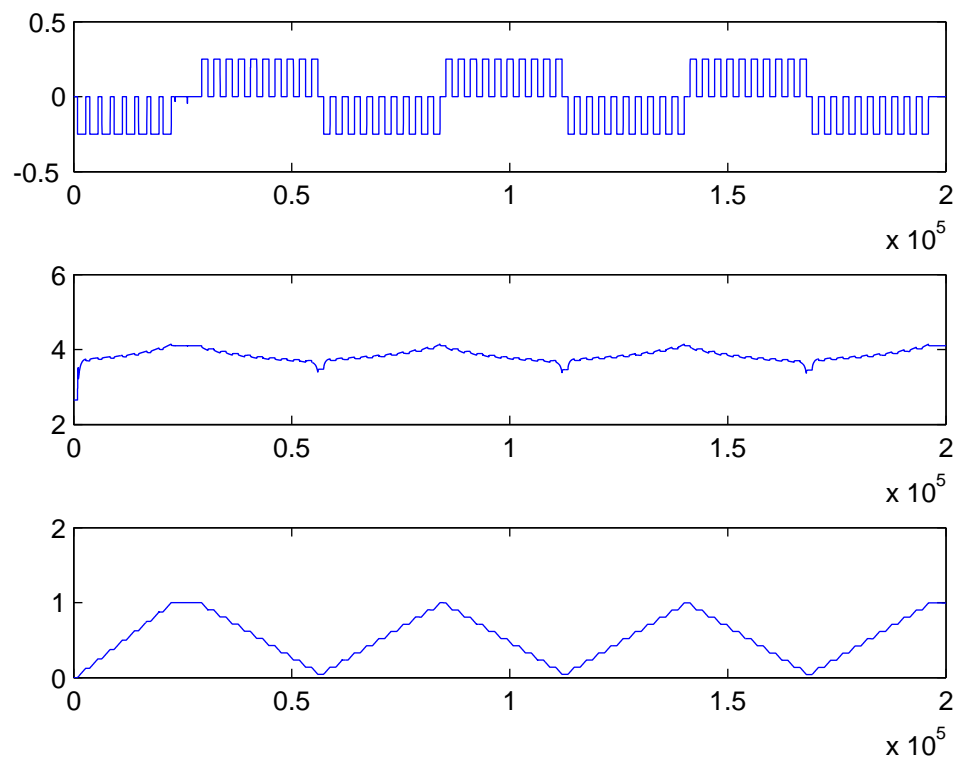
**Figure 2.2.** Discharge current along with the resulting voltage and SOC.

# Bibliography

[1] DOERFFEL, D. and S. A. SHARKH (2006) "A critical review of using the Peukert equation for determining the remaining capacity of lead-acid and lithium-ion batteries," *Journal of Power Sources*, **155**(2), pp. 395 – 400.

[2] CHIASSERINI, C. and R. RAO (1999) "A model for battery pulsed discharge with recovery effect," in *Wireless Communications and Networking Conference, 1999. WCNC. 1999 IEEE*, pp. 636–639 vol.2.

[3] JONGERDEN, M. and B. HAVERKORT (2009) "Which battery model to use?" *Software, IET*, **3**(6), pp. 445–457.

[4] CAPIZZI, G., F. BONANNO, and G. TINA (2011) "Recurrent Neural Network-Based Modeling and Simulation of Lead-Acid Batteries Charge-Discharge," *Energy Conversion, IEEE Transactions on*, **26**(2), pp. 435–443.

[5] SHEN, W., C. CHAN, E. W. C. LO, and K. CHAU (2002) "Adaptive neuro-fuzzy modeling of battery residual capacity for electric vehicles," *Industrial Electronics, IEEE Transactions on*, **49**(3), pp. 677–684.

[6] MANWELL, J. and J. MCGOWAN (1993) "Lead acid battery storage model for hybrid energy system," *Solar Energy*, **50**(5), pp. 399–405.

[7] RAKHMATOV, D. N. and S. B. K. VRUDHULA (2001) "An Analytical High-level Battery Model for Use in Energy Management of Portable Electronic Systems," in *Proceedings of the 2001 IEEE/ACM International Conference on Computer-aided Design*, ICCAD '01, IEEE Press, Piscataway, NJ, USA, pp. 488–493.

[8] CHEN, M. and G. RINCON-MORA (2006) "Accurate electrical battery model capable of predicting runtime and I-V performance," *Energy Conversion, IEEE Transactions on*, **21**(2), pp. 504–511.