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Valve Regulated Lead Acid battery float service life estimation using a Kalman filter

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ABSTRACT

A Kalman filter is developed from a model which characterizes the float service life of a battery into two phases. Once the latter phase of the float service life, that time when the capacity begins to decrease rapidly, has been detected the Kalman filter is started. Outputs of the filter are a smoothed version of the battery capacity and the projected capacity at specified time intervals in the future. It is this project ahead step that is used to estimate the remaining float service life of the battery.

1. Introduction

The float service life of a battery can be divided into two distinct periods as is depicted in Fig. 1. The first period is that time during which the loss of capacity is small. This can be thought of as a threshold or guarantee time. The second is characterized by a much more rapid decrease of capacity over time and continues until there is no useable capacity remaining. The length of the first period is determined by several factors, one of which is the discharge rate used in the test or application. The lower the discharge rate the longer will be the time of this portion of float service life. The duration of the second period is governed more by the battery design and the particular mechanism controlling life.

In most float service applications, such as a UPS, an important feature of battery management is the ability to estimate the time remaining for the battery to reach end of life. One method, developed for this task, is to use the project ahead step in a Kalman filter loop to estimate the remaining life of the battery. With a suitable model of the capacity degradation process during the second period of float service life, it is possible, after each measurement of capacity, to estimate the capacity at a specified point in the future.

The use of a Kalman filter for state-of-charge (SOC) applications has been described in several published papers in recent years. Chief among these is the series by Plett [1–3] and Vasebi et al. [4]. The models assumed, to which the Kalman filter is applied, are for the most part based on known physical principles or properties of a particular battery chemistry. In some cases electrical circuit analogues of the electrochemical charge/discharge processes are developed for the battery chemistry of interest.

In contrast to the approaches summarized above the track taken in this work is based on observed behavior of the degradation of capacity of a VRLA battery in float service operation. A probability distribution is identified that matches this observed behavior. This distribution is recast as a system of linear differential equations from which the Kalman filter is obtained.

The sections following will describe the model to be used, the formulation of the Kalman filter from this model and results obtained applying this method to actual float service life data.

2. Capacity degradation model

In a float service life application, as a battery ages, two mechanisms govern the rate of degradation of capacity, grid corrosion and loss of electrolyte. It is important to develop an understanding of the process by which physical measurements, in this case the pairs (capacity, time in float service), can be incorporated into a probabilistic setting. The benefit is, it allows the methods of probability and statistics to be used to explore the data and perform analyses to determine whether a relationship exists between the measurements. Furthermore, it may be possible to identify the underlying distribution which might adequately describe the relationship.

Imagine now taking a sample, of some size, of a particular manufacturer's battery and placing them into the same float service application. At some interval, not necessarily periodic, the batter-

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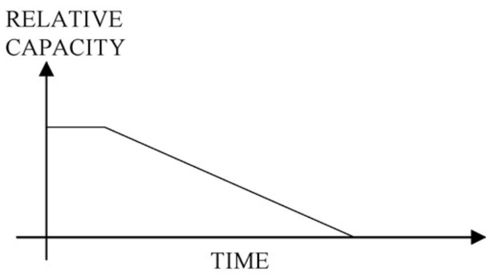

Fig. 1. Relative capacity vs. time of VRLA battery.

ies are discharged using a prescribed set of conditions (load and end voltage). The capacity (or discharge time) is measured and recorded together with the operating time of the battery. This is repeated until the capacity of each battery has diminished to a point where they are no longer useful. At the end of this exercise one will have a collection of battery capacities and operating times for each battery.

One possible use of the data is to make some estimate of the length of the float service life of this battery model. That is, how long will the battery operate before its capacity decreases to some specified value, generally given as a percentage of the rated or initial capacity. The first step in this process is to normalize the capacity (or discharge time) measurements. The method used here is to divide every capacity measurement, from each battery in the sample by a reference value, chosen generally from prior test data, to be slightly larger than the largest capacity in the sample. The result will be a collection of relative capacities, κ, where $0<\kappa<1$.

Consider now any of the particular points in time at which the sample of batteries is discharged. There will be a range of (relative) capacities measured that correspond to the time on test when the discharges were conducted. It is helpful to think of these different capacities as being due to different ages of the battery. A battery with a relative capacity of 0.83 has not aged as much as another in the sample with a relative capacity of 0.79. In other words the rates of aging are different for these two batteries since they have both been on float for the same amount of time. Hence one would expect the float service life of the first battery to be longer than that of the second. Continuing along this line of reasoning allows the age of the battery to be treated as a random variable.

Now it is possible to formulate the relative capacity and time on test in a probabilistic statement:

$$k_i = Pr\{L \le L_i\} = 1 - Pr\{L > L_i\}. \tag{1}$$

The relative capacity equals the probability that the age of the battery, L, is less than or equal to the accumulated time on float at the ith discharge, L_i. The expression $\Pr\{L \le L_i\}$ is the cumulative distribution function. The remaining work is to find a distribution whose properties match those of the data collected. In [5] the extreme value distribution was found to adequately represent the capacity degradation process. It is of the form:

$$F^{-1}(\kappa) = a_1(L - L_0) + a_0. \tag{2}$$

Here

(i) L_0 is the length of the first period of the float service life;
(ii) L is the age of the battery; $L - L_0 \ge 0$;
(iii) parameters a_1 and a_0 are estimated from the data;
(iv) $F^{-1}(\kappa)$ is the inverse distribution function, $F^{-1}(\kappa) = \ln[-\ln(1-\kappa)]$.

The model in (2) defines a random process. To design the Kalman filter a representation of the random process in terms of a system of linear differential equations must be developed first. This will be shown in the following section.

3. Kalman filter formulation

A Kalman filter is an algorithm for obtaining a minimum mean-square error point estimate of a random process. It is a method of least squares filtering that is obtained from a state space formulation. To start it is necessary to recast (2) as a system of linear differential equations. Note that (2) is just a linear equation in the variable L, with slope a_1 and y-intercept a_0. For this model let:

$$y(L) = a_1(L - L_0) + a_0. \tag{3}$$

Then carrying out the following steps let

$x_1 = y(L)$
$x_2 = \dot{y}(L) = \dot{x}_1$
$\dot{x}_2 = \ddot{y}(L) = 0$
$y(L_0) = a_0$
$\dot{y}(0) = a_1$

The resulting system of linear differential equations from these operations is

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \tag{4}$$

The discrete version of the state transition matrix can be obtained from (4) and is of the form:

$$\phi(\Delta t) = \begin{bmatrix} u(\Delta t) & \Delta t \\ 0 & u(\Delta t) \end{bmatrix} \tag{5}$$

where $u(\Delta t)$ is the unit step function.

The Kalman filter equations or loop are listed in (6)–(10) and following these the initial conditions will be developed. Following initialization, the sequence of steps, (6)–(10) are executed in the order shown. After the last step the process is repeated using the quantities from the project ahead step as inputs to start the loop again.

Start filter

(1) Compute Kalman gain:

$$K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} \tag{6}$$

(2) Update estimate with measurement z_k:

$$\hat{x}_k = \hat{x}_k^- + K_k[z_k - H_k \hat{x}_k^-] \tag{7}$$

(3) Compute error covariance for updated estimate:

$$P_k = [I - K_k H_k] P_k^- \tag{8}$$

(4) Project ahead:

$$\hat{x}_{k+1}^- = \phi_k \hat{x}_k \tag{9}$$

$$P_{k+1}^- = \phi_k P_k \phi_k^T \tag{10}$$

Some of the terms in (6)–(10) can be defined without too much explanation.

$z_k = \begin{bmatrix} y(L_k) \\ a_1 \end{bmatrix}$: measurement of normalized capacity, $y(L_k)$, and slope, a_1;

$x_k = \begin{bmatrix} x_{1k} \\ x_{2k} \end{bmatrix}$: state vector at t_k;

$H_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$: matrix defining the relationship between the measurement and the state vector.