Modeling of Lead-Acid Battery Capacity Loss in a Photovoltaic Application

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Abstract

We have developed a model for the probabilistic behavior of a rechargeable battery acting as the energy storage component in a photovoltaic power supply system. Stochastic and deterministic models are created to simulate the behavior of the system components. The components are the solar resource, the photovoltaic power supply system, the rechargeable battery, and a load. One focus of this research is to model battery state of charge and battery capacity as a function of time. The capacity damage effect that occurs during deep discharge is introduced via a non-positive function of duration and depth of deep discharge events. Because the form of this function is unknown and varies with battery type, we model it with an artificial neural network (ANN) whose parameters are to be trained with experimental data. The battery capacity loss model will be described and a numerical example will be presented showing the predicted battery life under different PV system use scenarios.

Introduction

A rechargeable energy storage system is essential for making the power from a photovoltaic (PV) generator dispatchable. The energy storage device most commonly used in this situation is a lead-acid battery because of its widespread availability and relatively low cost. This overall system is generally considered to be optimally sized when, over the long term: (1) the photovoltaic component generates sufficient power to service the load as well as generate sufficient stored energy to service the load while the PV is not available, and (2) the energy storage device has enough capacity to avoid lengthy periods of time at deep discharge. However, cost constraints and the highly variable nature of the PV output, depending on location, season, weather, etc., make it impractical to overdesign the system enough to completely avoid periods of deficit charging.

In lead-acid batteries, in particular, it is known that loss of capacity can result from deep discharge use cycles and from chronic undercharging such as is commonly found in PV applications. This may eventually lead to battery failure. In this project, we model the behavior of the battery, particularly the damage introduced due to deep discharge events, using an ANN. The ANN uses exemplars, obtained experimentally or analytically, that

represent the system's behavior. The ANN parameters were initially set for this work using existing performance data on one type of lead-acid battery and are being refined with the results of more detailed tests using various deficit charge profiles.

PV/rechargeable energy storage model

The present investigation creates a framework for the analysis of rechargeable batteries acting as a component of a photovoltaic power supply system. The power supplied by the PV system is modeled as a stochastic process. Our approach uses a bivariate Markov process to simulate the two main components of the solar radiation. In addition the load profile is modeled as deterministic or stochastic, depending on its operating characteristics. The behavior of the rechargeable battery, in particular the damage introduced by discharge cycles, is modeled by means of an ANN. Data obtained experimentally serve as exemplars for training the ANN. At this time, only limited battery data that characterize damage associated with discharge periods are available. Therefore, these data were augmented with plausible, synthetic data for training.

All these elements are combined into a single framework to yield a stochastic model for the power supply/energy storage/load system. Figure 1 shows a schematic representation of this system. The model is
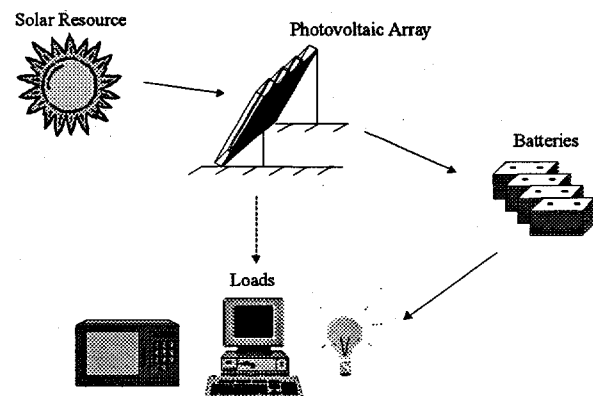

Figure 1: Power supply/energy storage/load system

operated on the Monte Carlo principle to yield realizations of the stochastic processes characteristic

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of the operational phenomena, and these can be analyzed using the tools of statistics to infer the probabilistic behavior of the system. Ultimately, the model can be used to design and optimize the power supply/energy storage/load system.

Artificial neural networks

A focus of this investigation is to use an ANN to model the damage caused in a rechargeable lead-acid battery due to extended discharge periods. Due to the complex behavior of a rechargeable battery, an explicit form relating the capacity loss to the depth and duration of a discharge cannot be easily derived. This is partly due to the expected variability in the results obtained from the different batteries that will be tested and partly due to the complexity of the electrochemical reactions involved in the process. It is then convenient to simulate the experimental data using a non-phenomenological modeling technique to find a relationship between the inputs and desired outputs. In this case, the output is the damage introduced to the battery due to discharge cycles and the inputs are the duration and depth of the discharge. Previous work, such as O'Gorman *et al.* [1] and Urbina *et al.* [2], have successfully demonstrated the modeling of primary and secondary battery systems using an ANN. In the following section, a brief presentation of the specific ANN algorithm used in this project is given.

The multivariate polynomial spline ANN

The multivariate polynomial spline (MVPS) network is an artificial neural network of the radial basis function type. The radial basis function ANN, which was developed by Moody and Darken [3], simulates mappings via the superposition of radial basis functions. Although the radial basis function ANN is an accurate local approximator, and it trains rapidly, it has the potential for size difficulties as the dimension of the input space grows. A generalization of the radial basis function ANN is the connectionist normalized linear spline (CNLS) network. This was developed by Jones et al. [4] and seeks to simulate a mapping by using radial basis functions in a higher order approximation than the radial basis function network. The MVPS network generalizes the CNLS network to multiple output dimensions and higher degree local approximations. The development of the mathematical framework behind the MVPS network is presented in detail in [5].

To summarize the development of the MVPS, let X be an n-dimensional input vector to the system being modeled, and let Z be its corresponding m-dimensional output vector. A locally accurate polynomial model approximates the mapping from X to Z in a region of the input/output space. The local models are superimposed.

Ultimately, we approximate the mapping of interest with the following parametric expression:

$$g(X) \cong \frac{\sum_j \left[A_{0j} + A_{1j}\left(X - C_j\right) + A_{2j}\varsigma\right] w(X, C_j, \beta)}{\sum_j w(X, C_j, \beta)} \quad (1)$$

where A_0, A_1 and A_2 are the coefficients of the local models, C_j is the "center" of the jth local approximation (also referred to as center vector or center), ς contains the quadratic and cross terms obtained from the elements in X, β is a parameter related to the width of the radial basis function and $w(X, C_j, \beta)$ are the weights attached to the local models (in this case a multivariate Gaussian probability density function is chosen as the weighing expression). Equation 1 is the parametric form of the multivariate polynomial spline ANN.

The MVPS network is used in the feed forward operation by specifying the input vector X, evaluating the weights w, calculating ς, substituting the weights and ς into Equation 1, and evaluating the output $g(X)$. This output is an interpolation among the training outputs. Note that the range of the summation index j is not specified in Equation 1. It is clear that the summation should be carried out over those local models nearest the input vector X. In the present code a user-defined number of local models is used and the ones nearest, in Cartesian space, to the input vector are chosen to make each prediction. Using the MVPS ANN, we developed a model to represent the damage that accumulates in a lead-acid battery when exposed to periods of deficit charging.

Lead-acid battery damage model

The objective of the rechargeable battery portion of the power supply model is to simulate the loss of capacity of the battery with time as it is subjected to a cycling environment typical of photovoltaic applications. In addition to the normal wear out of the battery that occurs as a function of number of cycles, depth of discharge, discharge rate, and temperature, batteries are frequently exposed to periods of deficit charging in PV applications. These accelerate degradation of capacity in lead-acid systems due to sulfation of the battery plates. It is assumed in this study that deficit charging is the major factor causing accelerated loss of capacity and therefore shortened life of batteries in PV power supplies. Experimental measurements will be aimed at determining what particular deficit charge conditions have the greatest effect on capacity loss. Two parameters were selected to characterize the deficit charge, namely maximum depth of discharge, D, and the duration of the discharge, T. Figure 2 shows these variables.
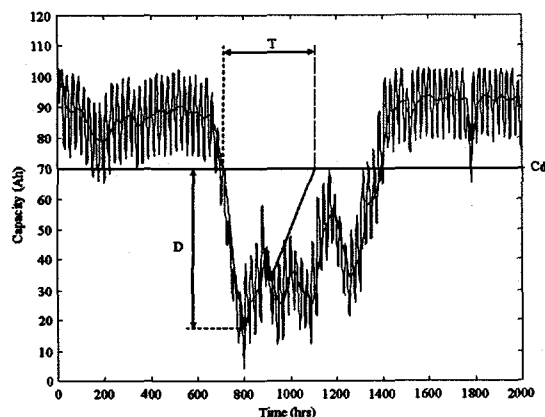
Figure 2: Definition of depth and duration of discharge

Figure 3: Proposed battery damage model

The maximum depth of discharge, D is defined as the deepest discharge, (as measured from a reference threshold, C_d) encountered during a deficit discharge event. The duration of the discharge, T is defined as the time it takes to bring the capacity back to the reference level, C_d (this is a function of the amount of solar insolation available). A moving average was used to represent the average daily capacity at any time.

Initial calibration of the battery damage model draws on data collected in previous experiments at the Florida Solar Energy Center (FSEC). For details on these tests see [6]. Although these data give some indication of the reduction in cycle life that occurs due to extended times at low state-of-charge (SOC), there are too few data points to completely define the battery damage surface. Consequently, a new set of deficit charge cycle tests has been planned that will provide a large enough data set to complete training of the ANN.

The focus in the new tests is to be on the damage due to deficit charging, so only a single discharge rate, C/20, will be used. Also only a few sustaining cycles will be run before and after the deficit charge region before measuring the capacity loss. Batteries will not be cycled to end-of-life. This will shorten the experiments to a few weeks maximum and will allow a greater variety of deficit charge characteristics (depth and duration of discharge) to be examined. Complex impedance data will also be collected to investigate whether small amounts of battery degradation can be detected earlier in the tests by this method.

Figure 3 shows the theoretical battery damage model which we simulated using an MVPS ANN. As experimental measurements of battery capacity loss are completed, the ANN description of the damage surface can be easily updated and refined. It is important to note that although reasonable, this initial model is based only on limited data and will be revised as more detailed experimental results become available.
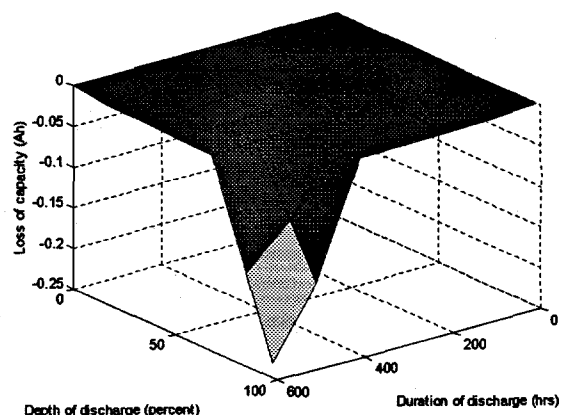
Test case and results

A test case was set up and the PV/rechargeable battery/load model was operated on the Monte Carlo principle to yield realizations of the solar insolation stochastic processes. The test case consisted of a PV array located in Albuquerque, NM (latitude 35° 03'), the tilt angle was set at 50° and the azimuth angle was set at 0°. The PV array was rated at 6.9 amps. It services a load that will be operated constantly during the night and at random intervals during the day. This load profile requires an average of 30 Ah per day. In addition, a 105 Ah lead-acid battery will be connected to the system. It will be assumed that the capacity threshold, C_d below which a discharge will start to cause damage is 70 Ah. As described in the previous section, the surface shown in Figure 3 was simulated using a multivariate polynomial spline ANN. The following results were obtained using simulated PV data based on 10 years of actual insolation measurements for this location.

Figure 4 shows a time history for one simulated year of capacity data (shown as a solid line) and the maximum potential capacity, M (shown as a dashed line). M is the initial capacity minus the irreversible capacity loss that accumulates due to deep discharge events and also due to regular daily cycling. As expected, there is a drop in the maximum potential capacity where the deep discharges occur. This is consistent with our ANN model shown in Figure 3. That is, more damage is introduced to the battery during deep discharges for long periods of time.
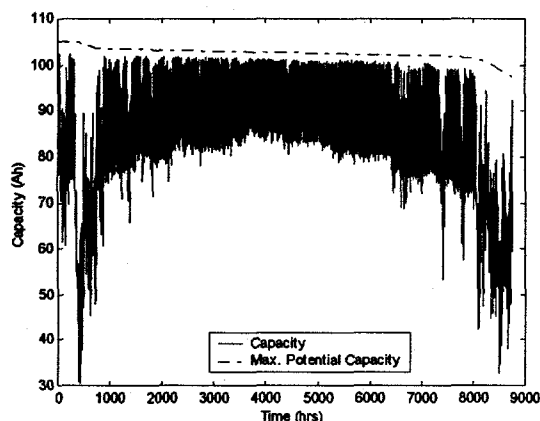
Figure 4: Capacity simulation using a random load

A first passage probability analysis was performed and it is shown in Figure 5. This shows the probability that a battery passes a certain capacity threshold at any given time. From the figure we notice that by approximately 3000 hours of operation, the battery's maximum potential capacity will be below 99% of the initial capacity. By the end of one year of operation, there is about a 65% probability that the battery will be at or below 90% of the initial capacity and about 55% probability that it will be at 80% or less of the initial capacity. This type of analysis allows us to make decisions such as when the optimal time to replace a battery has been reached and how to size the PV/battery system to achieve the desired reliability for a particular application.
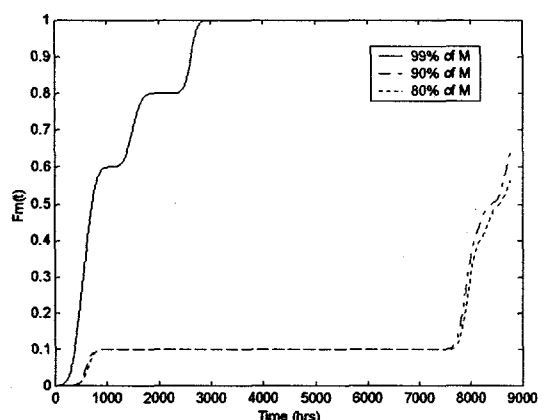

Figure 5: First passage probability of M

Summary

A comprehensive stochastic model for the analysis of a renewable power supply/energy storage/load system has been developed. Several mathematical modeling techniques, which included stochastic, deterministic,

and artificial neural network models, were used to develop this capability. These models were combined and solved simultaneously in the Monte Carlo framework to generate realizations of the system behavior. The rechargeable lead-acid battery capacity is modeled using a combination of phenomenological and ANN models. The interrelation of the duration and depth of discharge is mapped to the damage caused to the battery as represented by a diminution of the maximum potential capacity. Validation of the proposed ANN model will be necessary once more detailed experimental data are obtained. In addition, a first passage probability analysis was performed to demonstrate the capability of the PV power supply system model. The reliability of the system was assessed given a specific set of parameters and a load profile. These results also show how the model can be used to guide decisions regarding maintenance or battery replacement.

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