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Cycle Life Prediction of Battery-Supercapacitor Hybrids Using Artificial Neural Networks

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The cycle life of batteries and battery-supercapacitor hybrid systems was predicted using artificial neural networks. The presented techniques are able to predict the cycle life of a device based on a short (around 4% of the average cycle life) initial segment of the discharge curve. The prediction showed good performance with a correlation coefficient above 0.95. We were able to improve the predication further by considering readily available measurements of the device and usage.

Introduction

There is a pressing need in energy storage to meet the ever increase demands for sustainable energy. Batteries, supercapacitors, and their hybrid combination are all significant contributing technologies. Hybrid systems containing a battery and a supercapacitor have been experimentally demonstrated to exhibit longer operating times when compared to systems with batteries alone under high load and high current pulse conditions [1-5].

Being able to predict the lifetime of a power storage device is of immense technical and commercial importance when planning systems, selecting the most suitable battery, determining the operating conditions, and planning replacement intervals for batteries [6]. An important question is how long will a battery of a specific type and manufacturer last under certain operating conditions and how will the lifetime be affected if the operating conditions were changed?

The cycle life of a battery is the result of the ageing processes ongoing within the battery. These ageing processes are irreversible changes in the components of a battery or changes in the materials used or in the properties of the battery [6]. These ageing processes can be seen as being induced or furthered by stress factors, such as a battery remaining a long time at low states of charge, Ah throughput, the charge factor, the time delay between full charges, or the operating temperature. Battery cycle life prediction typically attempts to develop quantitative models capturing the relationship between stress factors and ageing processes. Developing such models is complicated by that typically operating conditions, such as ambient conditions, user requirements, operating regimes, and battery design lead to a combination of stress factors and that, therefore, multiple ageing process have to be considered simultaneously. The multiple ageing processes may interact and interfere with each other. It is even more complicated to predict the cycle life of hybrid energy storage system as the effects of ageing involve the complete system, not just the battery cell.

In contrast, rather than deriving such model from physical relationships, estimation techniques attempt to infer a set of parameters for the model to minimize the sum of squared differences between the observed behavior (target) and the model-generated output. Artificial neural networks (ANN) are an effective estimation technique to approximate the parameters for complex non-linear behavior for a combination of functions of the form $a = f(\mathbf{Wp} + b)$, where **p** is a vector of inputs, **W** is a vector of weights, b is a bias which is summed with the weighted inputs, and f is the transfer function applied. By combining such functions in series, that is, linking the output of one function to the input of another, and/or in parallel, that is, by applying an input to a set of such functions concurrently, one can approximate arbitrarily complex non-linear functions. ANN estimate the values of the weight parameters in these functions so that the combined set of functions yields the desired output, given its input.

An ANN is composed of a set of processing elements, referred to as neurons, which each correspond to a function from some inputs to an output, as described above, see Figure 1. The nodes of an ANN are grouped in an input layer, a number of hidden layers, and an output layer. Each input to the ANN is processed by a neuron in the input layer, each output is processed by a neuron in the output layer, and an arbitrary number of additional neurons may be inserted in hidden layers. There is no physical meaning to the neurons in the network or to the architecture of arranging the network into layers and connecting the individual neurons. Through a training process, the weights and biases in the individual neurons are iteratively adjusted so that the overall network minimizes the sum of the squared differences between predicted outputs and observed outputs given a known set of training data. A number of algorithms have been developed to perform this adjustment efficiently while avoiding to be trapped in local minima.

Since ANN can discover relationships between inputs and outputs of a system without a detailed understanding of the mechanisms involved, they can be effectively applied to estimate models for systems where such relationships are not clearly understood. Macdonald et al studied the effect of temperature and running history (current, time step, time from start of test, ampere-hours, etc.) of a battery on its output

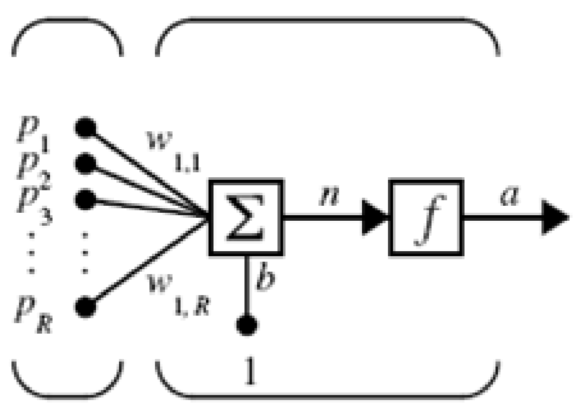

Figure 1 Schematic depiction of a single neuron (processing element) of an ANN. The weighted inputs and the bias are summed (Wp + b) and a transfer function f is applied to the result, yielding the output of the neuron.

voltage [7]. Gorman et al utilized ANN to simulate a single load constant discharge curve [8]. Grewal et al investigated the effects of pulse current loads on the discharge time of a Li-ion battery and used a three-layer feed forward ANN to successfully simulate the state of discharge of the battery [9]. Farsi et al used ANN to predict supercapacitor performance, such as exchange current densities, energy and power densities, with good correspondence between predictions and a numerical model [10].

In this paper, we present an effective technique based on ANN to predict the cycle life of energy storage systems, both batteries and hybrid systems comprised of batteries and supercapacitors.

Experimental

The batteries used were commercial primary batteries with a rated capacity of 1000 mAh. The supercapacitors (Taiyo Yuden, purchased from Digi-Key Co.) had a rated capacitance of 2 F, voltage of 2.3 V, and ESR of 50 mΩ. The equivalent series resistance (ESR) of batteries and supercapacitor was measured on a Solartron 1255 frequency response analyzer interfaced with an EG&G 263A. The batteries and battery–supercapacitor parallel systems were discharged on a Maccor battery test system. A high current pulse discharge was applied, with the pulse discharge load set at 1.5 A, 2 A or 2.5 A. The pulse width of the current was fixed at 0.5 s. The duty ratio was set at either 0.17 or 0.25. The cut off voltage was set at 1 V. All tests were conducted under ambient conditions. In all experiments, we used both batteries and battery-supercapacitor hybrids together.

We constructed an ANN to predict the number of discharge cycles before the voltage of the device drops below the cut off voltage based on inputs characterizing the device and operating conditions. We used a three layer ANN comprised of an input layer with a neuron per input, a hidden layer, and a single neuron in the output layer which represents the predicted number of discharge cycles. The number of neurons in the hidden layer was selected based on the number of input neurons, following the rule of thumb to set the size of the hidden layer to roughly twice the size of the input layer.

For training the ANN we used the Levenberg-Marquardt back propagation algorithm which is an efficient implementation of a quasi-Newton method to estimating the network parameters. In order to improve generalization of the network and to avoid overtraining, we relied on the *early stopping* technique: A set of validation data is monitored during training. Initially, both the error in the training data and the error in the validation data decrease. When the network begins to overfit the data, the validation error increases. At this point, training is stopped.

In all our experiments, we divided the available data into three distinct data sets: training data, validation data, and test data. The network was trained with the training data, using the validation data to determine when to stop training. The trained network was then evaluated using the test data. As parameter estimation through ANN is a stochastic process, in each experiment the network was trained and evaluated 100 times, and the average obtained result was chosen. In this way, we avoided tainting the obtained results by accidentally good or bad performance on specific samples.

Results and Discussion

In an initial experiment we attempted to predict the cycle life, that is, the number of discharge cycles at which the voltage of the battery or battery-capacitor system drops below 1 V, from known characteristics of the devices. For these experiments, we used ESR, duty ration, and information as to whether the device was a battery or a hybrid as the input to the neural network. The neural network was configured with 3 input nodes, one for each of these characteristics, and a single output node indicating the predicted cycle life. The network performed best with 3 hidden nodes. Figure 2 shows the performance of the ANN predicting the life cycle of the systems based on known device characteristics only. As can be clearly seen, the performance of the network is rather poor: the slope of the correlation of predicted values vs. observed values is only 0.1916, far from indicating a good match, and the correlation coefficient is below 0.5.

The cycle life of a battery is the result of the ageing processes ongoing within the battery. The aging processes can be linked to stress factors [6]. Stress factors are the result of operating conditions, such as ambient conditions, user requirements, operating regimes, and battery design. [6] describes stress factors as statistical parameters calculated from a time series of operating conditions and link the operating conditions to the observed cycle life. We then assumed that this linkage between operating condition and cycle life is summarized in the discharge curve. That is, rather than trying to infer the relationship between stress factors and cycle life, we attempted to infer the relationship between the shape of the discharge curve and the cycle life. If the discharge curve correctly summarizes this linkage, then we would be able to predict the cycle life of the battery. Such prediction is only useful if it can be made based on a relatively short initial segment of the overall discharge curve.

To predict the cycle life from the initial segment of the discharge curve, we configured the ANN with input nodes corresponding to the voltage measured at a given point of the discharge curve. We sampled the discharge curve every 5 cycles. For

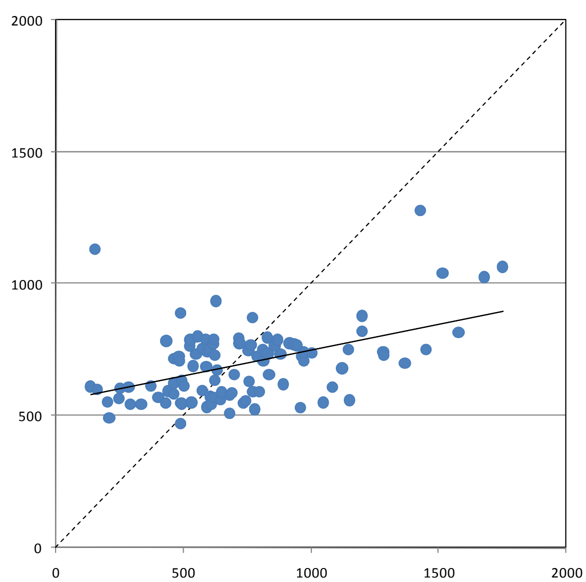

Figure 2 Predicted cycle life based on readily measurable device characteristics (ESR, duty ratio, hybrid vs. battery) at 2.0 A pulse discharge. The horizontal axis shows the predicted cycle life; the vertical axis shows the actual cycle life.

example, to leverage the first 100 cycles of the discharge curve, we set up the ANN with 20 input nodes, reflecting the voltage at the 5^{th}, 10^{th}, 15^{th}, up to the 100^{th} cycle. We experimented with various configurations of hidden nodes, from 1.5 to 2.5 times the number of input nodes. The single output node holds the prediction of the cycle life.

Figure 3.(a) shows the predictions obtained when varying the number of hidden nodes and the initial length of the discharge curve, at a current of 2 A. The horizontal axis shows the initial length of the discharge curve in terms of the percentage of the average cycle life. The vertical axis shows the correlation coefficient of the obtained prediction. The different points for a given initial length of the discharge curve result from differently configured nets (using different numbers of hidden nodes). Not surprisingly, the prediction improved with the length of the observed discharge curve. As the length of the initial segment increased, the impact of the chosen configuration of the net became smaller (showing a smaller spread of the correlation coefficient). Figure 3.(b) shows only the best results for each chosen initial segment of the discharge curve. The predictions were quite good already at very short initial segments: at less than 2% of the average cycle life, the prediction showed a correlation coefficient above 0.93. The accuracy improved rapidly, and after 4% of the average cycle life was above 0.95. Above 8% of the average cycle life, the correlation coefficient exceeded 0.96. In Figure 4, we show the predictions at 4% of the average cycle life: the fit between predicted and observed values is very good, and the slope of the correlation line is 0.857, sufficiently close to 1. We then compared the predictions obtained for various levels of discharge current, at 1.5 A, 2.0 A, and 2.5 A, see Figure 5. We see that the accuracy of the prediction increased with the current applied. For example, at 4% initial length the correlation coefficient obtained for 2.5 A current was close to 0.98 (with a correlation slope of 0.916).

Our initial experiment had shown that we were not able to obtain good predictions from easily measurable device characteristics alone (see Figure 2). We then conducted an experiment to determine whether knowledge of these characteristics could further improve the predictions based on the initial segment of the discharge curve. We, therefore, added input nodes to the network reflecting these characteristics. Figure 6

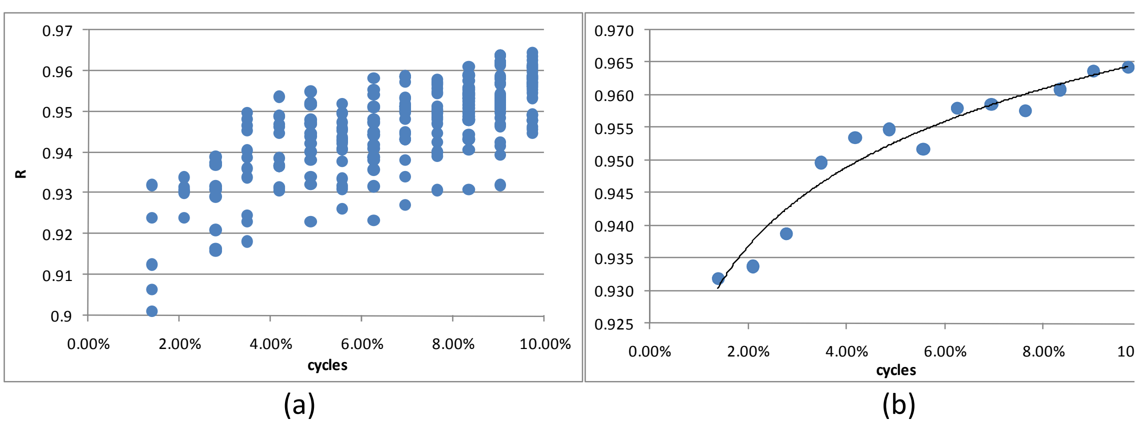

Figure 3 Prediction results at 2.0 A pulse discharge using different lengths of data: (a) with varying number of hidden nodes and (b) best prediction. The horizontal axis shows the length of the initial segment of the discharge curve in percent of the average cycle life; the vertical axis shows the correlation coefficient.

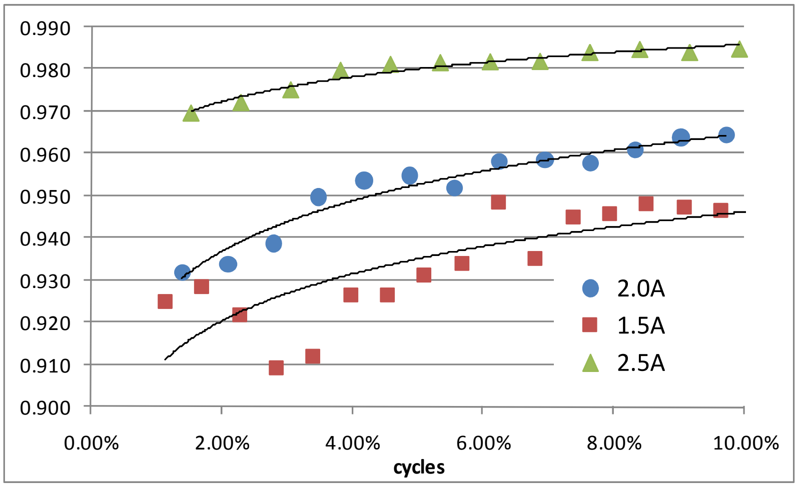

Figure 5 Prediction results at 1.5 A, 2.0 A, and 2.5 A pulse discharge (curves from bottom to top). Axes are as in Figure 3.

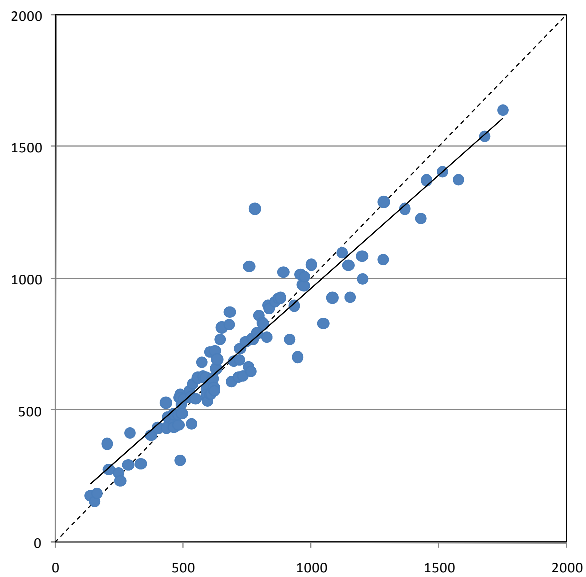

Figure 4 Predicted cycle life based on initial segment of the discharge curve of roughly 4% of the average cycle life at 2.0 A pulse discharge. Axes are as in Figure 2.

shows the predictions obtained using 4% of the average cycle life at a discharge current of 2.0 A, when providing additional knowledge of device characteristics. As can be seen, the information about the ESR had little impact on the prediction accuracy. Adding information whether a device is a battery or a hybrid improved the prediction somewhat. Knowledge about the duty cycle did improve the prediction more substantially; in fact, providing any additional information did not further improve the prediction. A similar improvement was obtained when providing information about both the ESR and whether the device was a battery or hybrid. We conclude that while most of the linkage between stress factors and cycle life is already reflected in the shape of the discharge curve, there are still aspects of this linkage that are provided by device characteristics.

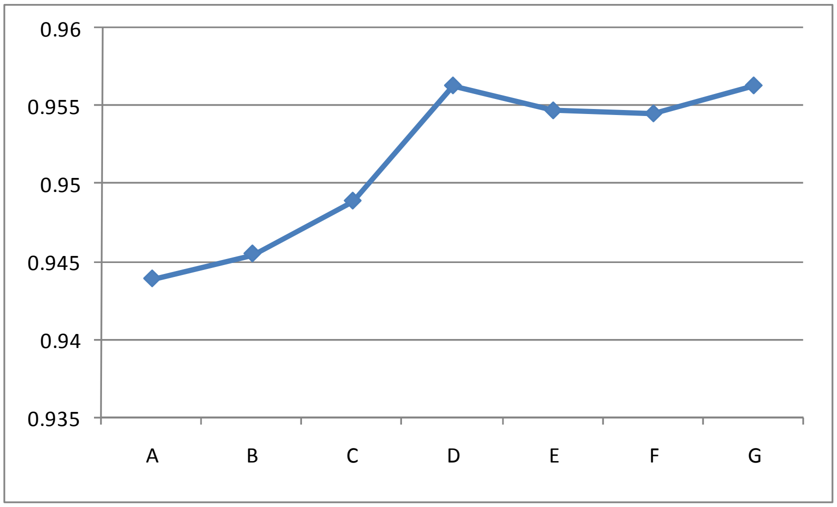

Figure 6 Best prediction results at 2.0 A combining the initial segment of the discharge curve of 4% of the average cycle length and readily measured device characteristics for discharge data only (A), including ESR (B), battery/hybrid (C), duty cycle (D), battery/hybrid and duty cycle (E), battery/hybrid and ESR (F), battery/hybrid, ESR, and duty cycle (G).

Predicting the cycle life of batteries and hybrid systems is essential for designing applications based on such power storage devices. Predictive methods based on models derived from the internal chemistry of the devices have not yet been proven. Although it is impossible to follow the discharge profiles of most batteries and/or hybrid energy systems in real life, some important information of these systems can be extracted from accelerated life tests such as constant current pulse discharge, which is a common practice for quality control with many battery manufacturers. However, this practice is time and energy consuming, in particular, for hybrid systems which further extend the life time of systems. Therefore, the proposed method of predicting cycle life based on a short initial segment of pulse cycle data is highly beneficial. To date, there are only a limited number of studies on the prediction of battery life, and even less for battery/supercapacitor hybrid systems. This paper developed a predictive method for energy storage systems (both battery alone and battery-supercapacitor hybrids).

Conclusions

An approach to predict the cycle life of battery and battery-supercapacitor hybrid systems using ANN has been demonstrated. Our results show that, relying on only a small fraction of the discharge data (less than 4%), the ANN can predict the cycle life of these devices and systems with very good accuracy. The key information required to predict the cycle life are already captured in the discharge data itself, which reflects both the physical characteristics of the device as well as the conditions of use, such as applied current, duty ratio, or whether the device as a battery or a hybrid system. ANN is a powerful technique to effectively predict the life and cycle behavior of energy storage devices and/or systems without requiring a detailed investigation of the internal chemistries and interferences between the chemistries of these devices.

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