

Fuzzy Logic-Based State-of-Health Determination of Lead Acid Batteries

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Abstract:

Determining the state-of-health (SOH) of uninterruptible power supply (UPS) batteries using impedance measurements has been demonstrated by several researchers. One such approach uses single frequency impedance measurements, which may not be reliable under all circumstances. Another approach employs measurements over a wide frequency range and uses extracted equivalent circuit parameters to correlate with battery SOH. This is a computationally extensive approach and not easily incorporated into a low cost system.

Over the last five years, Villanova University and US Nanocorp. have been jointly developing a patented fuzzy logic method for estimating the state-of-charge (SOC) and SOH of batteries. This methodology has proven to be both a simple and powerful means to model battery characteristics accurately and robustly.

In this paper we will describe how impedance measurements, combined with fuzzy logic data analysis have been used to estimate the SOH of lead acid batteries used in portable defibrillators. We will also propose ways in which this approach may be extended to estimating the SOH of UPS batteries.

1.0 Introduction

1.1 Defining Battery SOH

Battery state-of-health (SOH) is an important quantity to monitor for UPS batteries since they must perform reliably in critical applications. The SOH (or “state-of-condition”) of a battery may be defined in several ways, the precise definition depending on the particular application. For example, in the portable defibrillator application the number of high current discharge pulses that may be delivered by the battery is of paramount importance whereas in the UPS application, the available capacity of the battery is the parameter of concern. Another important issue regarding battery SOH is the ability to distinguish recoverable failure modes from catastrophic

failure modes. For example, a battery may be in a poor SOH because of a corroded electrode (a catastrophic failure) or may simply be suffering from a loss of capacity due to electrolyte stratification, which may be overcome through a period of overcharge allowing the full capacity of the failing battery to be recovered (a recoverable failure) [1].

1.2 SOH Determination Techniques

Many different techniques are used to estimate the state-of-charge (SOC) or SOH of a battery. The techniques generally fall into three categories:

- 1) Coulomb counting
- 2) Voltage recovery
- 3) Impedance measurements

In coulomb counting, the charge flowing into and out of the battery is monitored and the SOC estimated by determining how much charge has been removed from the battery compared to how much was available from the previous charging cycle. If the estimated charge capacity is compensated for variations in temperature and discharge rate, the coulomb counting approach can be quite accurate in determining the SOC of a battery. However, it provides little useful information on the SOH of a battery.

Voltage recovery is the common technique employed for estimating the SOH of UPS batteries. In this approach a load is applied to the battery and the voltage depression under load and the temporal recovery of the battery voltage after removal of the load are monitored and used to estimate the SOH of the battery. This method requires the battery to be physically removed from a string and tested off-line.

Impedance measurements are sometimes used to evaluate the condition of batteries. The basic ac impedance approach involves the measurement of the ac voltage response of a

battery when a small perturbing ac current is applied to the battery. This is typically done under open circuit conditions but may also be done on-line (under float conditions for UPS batteries). Usually a single frequency is used and the resulting battery condition is estimated from the value of the impedance at the single frequency [2]. A more sophisticated approach has recently been developed by Midtronics – the discrete frequency imittance spectroscopy (DFIS) approach [3]. In this method the battery’s ac impedance is measured at three different frequencies and this information is used to derive the complete spectrum of the ac impedance. This spectrum is then used to determine the equivalent circuit parameters of the battery which, in turn, are used to evaluate the SOH of the battery. Battery impedance characteristics are rich with information regarding the battery’s SOH but complex least squares analysis usually used to extract equivalent circuit parameters to determine battery SOH is computationally intensive.

In the present approach, fuzzy logic data analysis is used to estimate the SOH of a battery directly from measured battery data without any intermediate transformation steps. The technique is versatile enough to be used with any of the three interrogation techniques described above. Indeed a fuzzy logic method has previously been incorporated in estimating capacity of VRLA batteries by considering the voltage discharge profile in the coup de fouet region [4].

This approach also offers high accuracy, robustness, fast development time, and high code efficiency. The fuzzy logic approach is also generic and has been applied to a wide variety of battery chemistries including primary lithium sulfur dioxide, lithium manganese dioxide, nickel metal hydride, lithium ion, and lead acid [5-11].

In this paper we present an introduction to fuzzy logic, provide an example of applying the fuzzy logic technique to estimating the SOH of lead acid defibrillator batteries, and end with a description of how the approach could be used to estimate the SOH of UPS lead acid batteries.

2.0 Introduction to Fuzzy Logic

Data may be characterized in two ways: crisp or fuzzy. Crisp data describes data that is certainly indicated, e.g., a temperature of 50 °C. On the other hand fuzzy data is indicated in an uncertain way, e.g., the temperature is “warm”. The linguistic descriptor can cover a range of temperatures and the degree to which a crisp data point falls into the fuzzy set of “warm” is indicated by a quantity referred to as its “degree of membership” to the set “warm”.

Consider the range of possible temperature values as a set of all temperature. A subset of temperatures can be defined as the set of all temperatures between 20°C and 30°C. Let this

subset be referred to as the set of HOT temperatures. Obviously, a measured temperature value of 25°C can be categorized as a HOT temperature. Not so obvious is a measured temperature value of 22.5°C. Is this still a HOT temperature? If so, does it belong to the set of HOT temperatures as much as 25°C?

Bivalent set or crisp set theory says yes. Not only is 22.5°C a HOT temperature, but the degree to which it belongs to the set of HOT temperatures, or its membership value or bit value (binary unit), is identical to that of 25°C, both a value of one. It would have to be in accordance with the ‘1-0’ theory, i.e., either a one or a zero.

In contrast, a fuzzy set of HOT temperatures can be defined. This fuzzy subset can cover a range of temperatures as did the bivalent set, but now the degree to which a measured data point falls into the fuzzy set of HOT is indicated by a fit value (fuzzy unit) between zero and one.

The fit value is sometimes called the degree of membership. Fig. 1 shows examples of various fuzzy subsets or membership functions of the temperature. Depicted is the degree of membership of various temperatures to the fuzzy subsets COLD, WARM and HOT. The process of assigning membership functions to sets of data is referred to as fuzzification of the data.

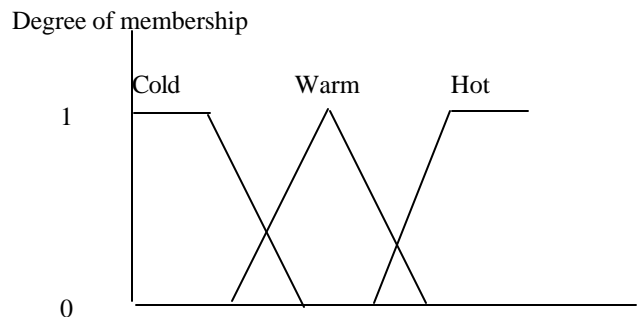


Fig. 1. Membership function for temperature

Fuzzy set theory provides a method to categorize measured data using linguistic variables such as cold, warm and hot. It accounts for the uncertainty inherent in such a linguistic description by using multivalued sets.

Fuzzy systems map measured inputs to desired outputs. They estimate functions by translating the behavior of the system into fuzzy sets and by using rules based on a linguistic representation of expert knowledge to process the fuzzy data. This offers a qualitative rather than a numerical description of a system. The linguistic representation presents an intuitive, natural description of a system allowing for relatively easy algorithm development compared to numerical systems. The ease of development of fuzzy logic

systems should not undermine their powerful capabilities in solving complex control and modeling problems.

A typical fuzzy system has four conceptual components:

- A rule base describing the relationship between input and output variables;
- A data base that defines the membership functions for the input and in the case of Mamdani modeling output variables;
- A reasoning mechanism that performs the inference procedure;
- A defuzzification block that transforms the fuzzy output sets to a real valued output.

The rules relating the input and output variables are written in an ‘if... then’ linguistic format, such as ‘if temperature is hot and discharge rate is high then SOC is low’.

The membership functions and rule set may be described by an expert or generated by the use of neural network algorithms. Unsupervised neural networks, such as the subtractive clustering algorithm, can find the initial rules and membership functions using numerical training data that describes the input/output relationship [12].

3.0 SOH of Lead Acid Portable Defibrillator Batteries

3.1 Experimental Procedure for Collection of EIS Data

A Solartron 1280B combined Frequency Response Analyzer (FRA) and Potentiostat/Galvanostat was used to collect the EIS data under control of Zplot (Scribner Associates.) The batteries tested were Medtronic- Physio-Control 2.5Ah 8V packs. All EIS measurements were performed in galvanostatic mode whereby a 100 mA sinusoidal current signal was applied to the battery and the resultant voltage was measured. An electronic load was used to discharge the battery by means of a simulated defibrillator pulse load profile. Details of the test procedure are as follows:

Test Procedure

- 1) EIS measurement over the frequency range of 1 Hz – 10kHz.
- 2) Constant current discharge at 1 A for 5 minutes.
- 3) Constant current discharge at 7 A for 10 seconds.
- 4) Rest at open circuit for 1 minute.
- 5) EIS measurement.
- 6) Repeat steps 2-5 until end-of-discharge reached (1.75 V/cell).

As can be seen from the test procedure, the simulated defibrillator pulse load profile consisted of a 1 A constant

current discharge for 5 mins followed by a 7 A constant current discharge for 10 secs. The magnitude and phase of the impedance as a function of “remaining number of simulated defibrillator pulses” or essentially battery SOC, may be seen for the 9th cycle (or when the battery is at a high SOH) in Figs. 3a-b respectively. Conversely Figs. 3a-b show the magnitude and phase of the impedance for the 57th cycle of the battery (or when the battery is at a low SOH.) Notice that the number of available simulated defibrillator pulses is about half of the number attainable at the 9th cycle even though initially the battery was fully charged (100% SOC)

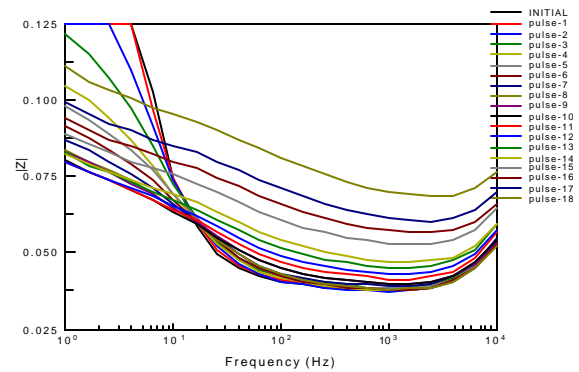


Fig. 2a. EIS, Magnitude of the Impedance $|Z|$ vs. frequency at various SOCs. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid, cycle 9.

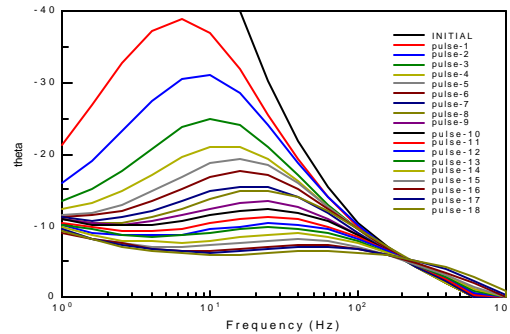


Fig. 2b. EIS, Phase Angle of the Impedance vs. frequency at various SOCs. Medtronic Physio-Control 2.5 Ah, 8 V, Lead Acid, cycle 9.

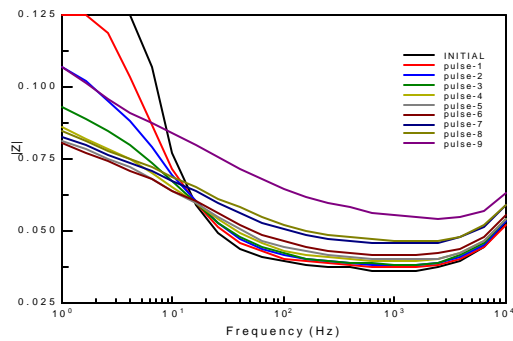


Fig. 3a. EIS, Magnitude of the Impedance $|Z|$ vs. frequency at various SOCs. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid, cycle 57.

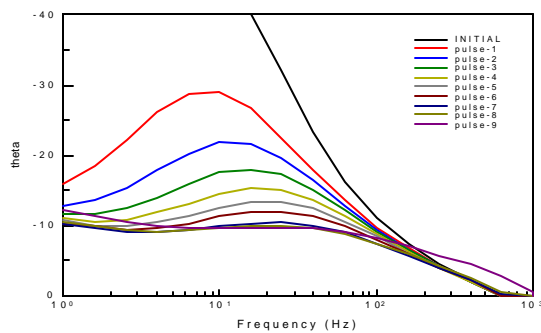


Fig. 3b. EIS, Phase Angle of the Impedance vs. frequency at various SOCs. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid, cycle 57.

during both discharge cycles. This is clearly an indication that the battery SOH has decreased.

3.2 Fuzzy Logic Modeling of Defibrillator Batteries

To make a low-cost, practical diagnostic system for automatic portable defibrillator batteries the acquired EIS data at various SOCs and SOHs must be reduced to a form that can be easily manipulated by fuzzy logic models. This involves finding one or more frequencies where the variation in the magnitude and/or phase angle of the impedance can provide “some discrimination” between the different SOCs at any SOH (remembering a key attribute of the FL approach is in the ease at which several related and/or unrelated measures, each containing only partial information of a particular state of a system, can be combined to predict the state of the system.) A fuzzy logic model was developed to predict the number of remaining simulated defibrillator pulses, given the cycle number of the battery. This approach can take advantage of existing methods to predict cycle number such as “smart battery” technology that stores this information with the battery. We have also performed some preliminary work to use the impedance data to directly yield the cycle number. However, that effort is not reported in this paper.

3.3 Fuzzy Logic Model to Predict the Number of Remaining Simulated Defibrillator Pulses

The fuzzy logic was developed using MATLAB[®] and the Fuzzy Logic Toolbox for MATLAB[®][13]. A 3-input, 1-output system was developed using custom algorithms to implement the Standard Additive Model (SAM) Inference method. For rapid model development clustering algorithms, sometimes referred to as unsupervised neural networks, were used to find membership functions and rules. The input membership functions are gaussian, while the output membership functions are singletons. The first two inputs to the model are the magnitude of the impedance at 160 Hz, Fig. 4a., and the phase angle at 16 Hz, Fig. 4b., while the third input is the cycle number. Impedance data at the various SOCs over the entire life of a particular battery (Battery 0009) was separated into a ‘training’ data set used to develop the model and a ‘testing’ data set used to test the generalization ability of the model by presenting data from the same battery not “seen” by the model during training. The results of the testing data can be seen in Fig. 5a. As shown the FL model can predict the number of remaining pulses within +/- 1 pulse. It is to be noted that the prediction error is relatively constant throughout the SOC of the battery, in other words, the confidence of the prediction doesn’t depend on the SOC of the battery. To further test the generalization ability of the model, data over cycles 15 –23 of a second battery (Battery 0008) was used for additional testing, the results of which are again within +/- 1 pulse as can be seen in Fig. 5b. Note, testing of Battery 0008 was stopped short due to premature battery (or internal fuse) failure.

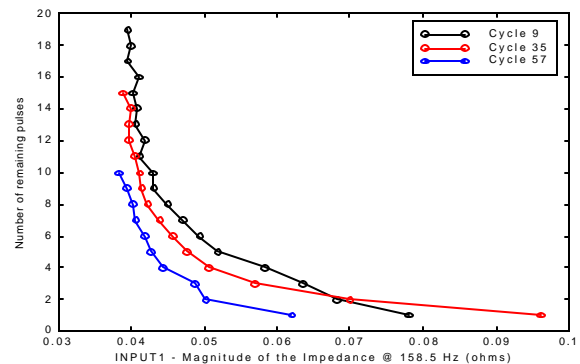


Fig. 4a. Fuzzy Logic Model, # of remaining pulses – Input 1, Magnitude @ 158.5 Hz vs. # of Remaining Pulses. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid, Battery 0009.

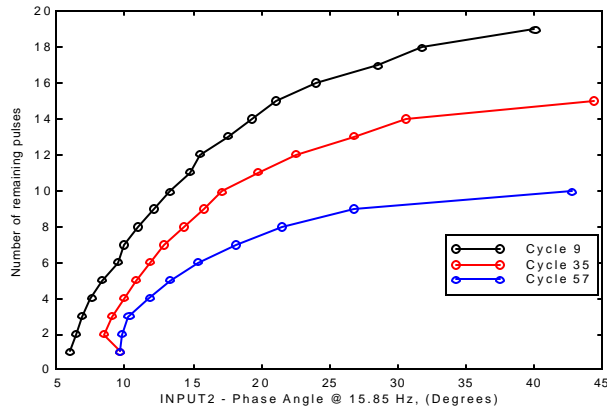


Fig. 4b. Fuzzy Logic Model, # of remaining pulses - Input 2, Phase Angle @ 15.85 Hz vs. # of Remaining Pulses. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid, Battery 0009.

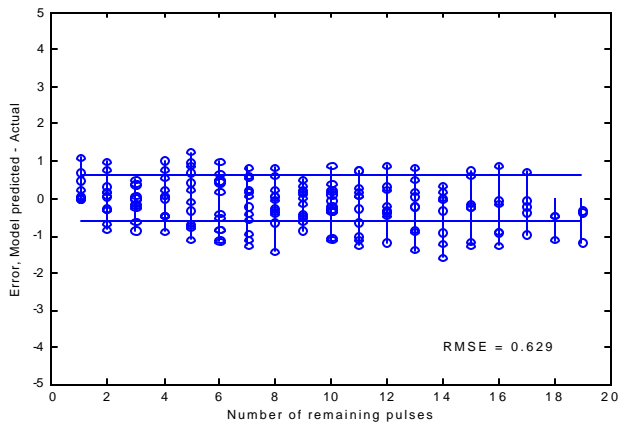


Fig. 5a. Fuzzy Logic Model, # of remaining pulses - Error. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid - Testing Data, Battery 0009.

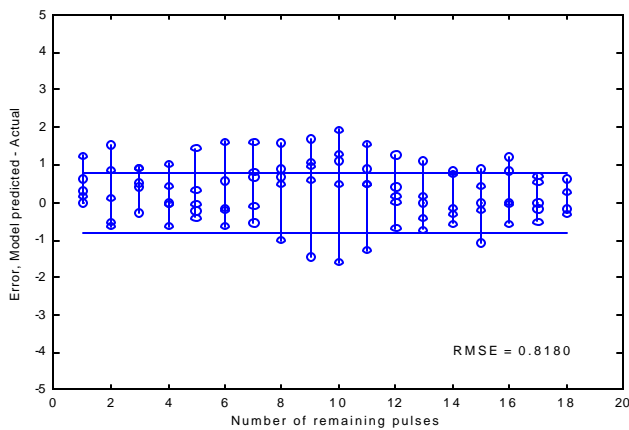


Fig. 5b. Fuzzy Logic Model, # of remaining pulses - Error. Medtronic Physio-Control, 2.5 Ah, 8 V, Lead Acid - Testing Data, Battery 0008.

Clearly the fuzzy logic model has performed accurately in predicting the number of pulses that the battery could deliver both in the case of batteries used to train the model as well as for batteries that were not used in model development. This demonstrates the robustness of the fuzzy logic approach to battery SOH estimation.

4.0 Sealed Lead Acid Batteries

Impedance measurements have also been made on sealed lead acid (SLA) cells and valve regulated lead acid (VRLA) batteries. The SOC of the SLA cells was modeled using a fuzzy logic approach.

Electrochemical Impedance Spectroscopy (EIS) data were collected on Hawker 2.5 Ah, "D"-size SLA cells. The EIS data was collected using the same instrumentation as used to collect defibrillator battery EIS data. analyze the data.

An initialization procedure consisting of 5 charge/discharge cycles was performed on each new cell. After completion of this initialization, EIS data were collected at various SOCs on each of four different cells. The following summarizes the experimental procedure followed for a fully charged battery:

Test Procedure:

1. Initial EIS measurement over the frequency range of 1 Hz – 65 kHz.
2. Galvanostatic discharge at 1 A for 15 mins.
3. Rest at open circuit for 30 secs.
4. EIS measurement.
5. Repeat steps 2-4 until end-of-discharge reached (1.69 V).

All EIS measurements were performed in potentiostatic mode whereby a 10 mV sinusoidal voltage signal was applied to the cell and the resultant current measured.

Figs. 6 a-b show the magnitude and phase angle, respectively, of the impedance vs. frequency for a typical cell at various SOCs. It was found that the magnitude and phase angle of the impedance at 10.3 Hz and the magnitude of the impedance at 103 Hz vary sufficiently with SOC so as to be adequate inputs for the FL model. Figs. 4 a-c show the variation of these FL inputs with SOC. This of course presupposes knowledge of what we ultimately desire to predict the cell's SOC. Therefore in order to find the actual SOC of the cell, a "back-calculation" is necessary.

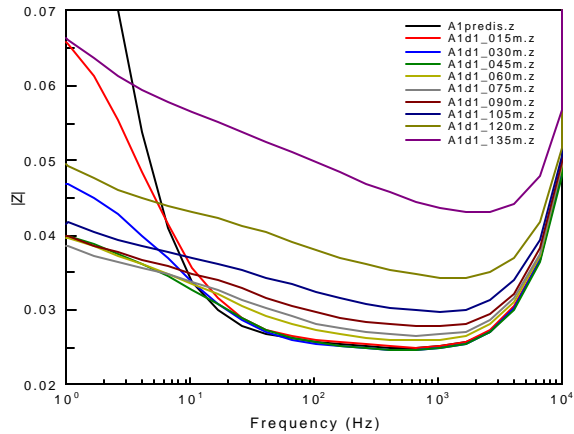


Fig. 6a. Magnitude of the Impedance $|Z|$ vs. frequency at various SOC's (Hawker Pb-acid, 2.5 Ah "D"-size cell).
 Note: predis is 100% SOC, _135m is 0 % SOC.

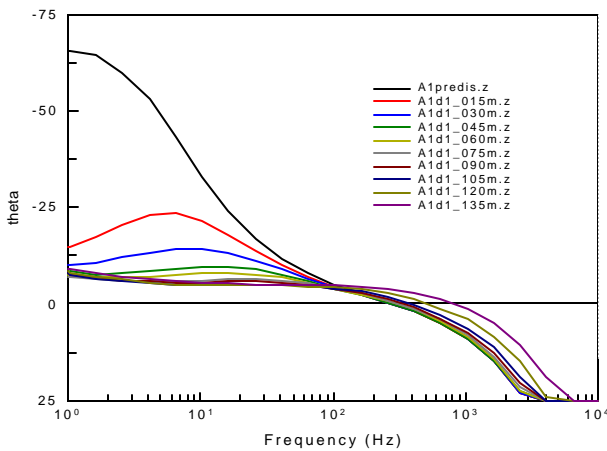


Fig. 6b. Phase Angle of the Impedance vs. frequency at various SOC's (Hawker Pb-acid, 2.5 Ah "D"-size cell).
 Note: predis is 100% SOC, _135m is 0 % SOC.

A 3-input, 1-output model was developed to predict the SOC of the cells based on the impedance data. The three inputs consisted of the magnitude and phase angle of the impedance at 10 Hz and the magnitude of the impedance at 100 Hz. A "training" data set was developed using the EIS data of one cell (cell "A"). Clustering algorithms were used to find the initial input membership functions, output functions, and the rules. Fine-tuning of the rules was performed by using gradient descent based learning algorithms. The model was then tested using two cells that were not used in the model development, cells "B" and "C". The capacity of cell "B" was ~ 78 % that of cell "A" while the capacity of cell "C" was similar to the training-set cell 'A'. As shown in Figs. 7 a,b, the model predicts the SOC of undocumented cells (*i.e.*

ones for which the fuzzy logic model had no prior knowledge of these cells' behavior) to within ~ 5%, which is especially good for Cell "B" considering its

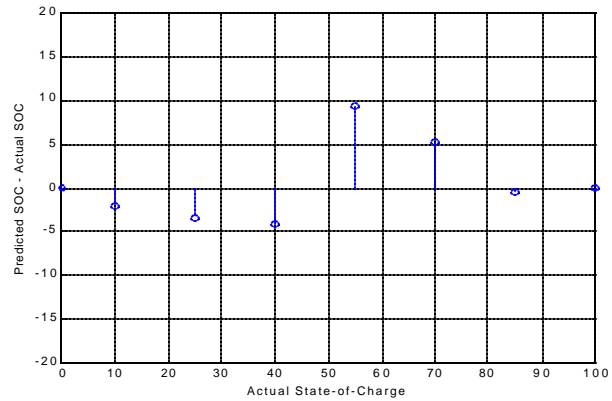


Fig. 7a. Fuzzy Logic Model Predicted SOC vs. Actual SOC. Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell "B". RMS Error = 4.2618

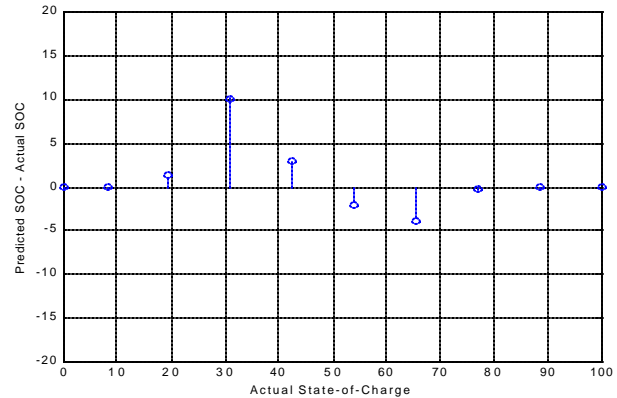


Fig. 7b. Fuzzy Logic Model Predicted SOC vs. Actual SOC. Hawker Pb-acid, 2.5 Ah, "D"-size, Cell "C". RMS Error = 3.6204

capacity was 22% less than the cell that was used for the model development! This again highlights both the accuracy and robustness of the fuzzy logic methodology.

Some preliminary EIS data has also been taken on C&D Broadband series 88Ah 12V VRLA batteries. These too were measured using the Solartron 1280 B in a galvanostatic mode using a similar procedure to that described for the SLA cells. These measurements were made following successive intervals of discharge at a C/5 rate following a rest period. The Bode plots for the magnitude and phase of the impedance at different depths of discharge measured on these batteries is shown in Fig. 8.

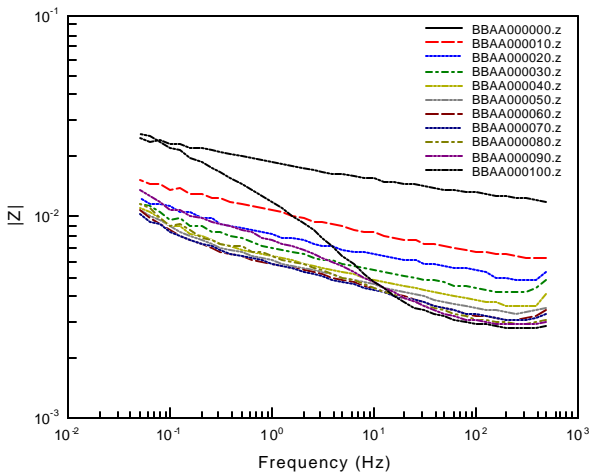


Fig. 8a Magnitude of impedance vs. frequency for 88Ah 12V C&D Broadband Series SLA Batteries

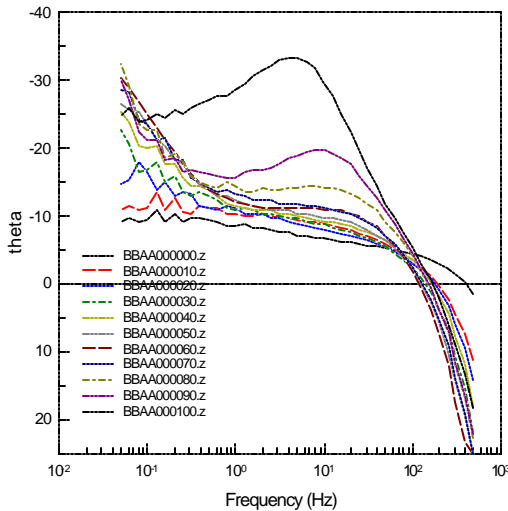


Fig. 8b Phase angle of impedance vs. frequency for 88Ah 12V C&D Broadband Series SLA Batteries

Just as previously seen in the other lead acid batteries, good separation of the curves at different depths of discharge is observed in the case of the VRLA batteries. No fuzzy logic modeling of this data has been performed on this preliminary data set to date but it is very amenable to such analysis.

Further work needs to be done in terms of measuring the impedance of the cells/batteries under different failure conditions so that fuzzy logic models may be developed to predict these failure modes. Such work has been performed by our group on small PEM fuel cell stacks where recoverable failure modes were predicted using a combination of ac impedance measurements and fuzzy logic data analysis even in fuel cell stacks that were not a part of the training set for the fuzzy logic models [14].

5.0 Conclusions

Fuzzy logic combined with ac impedance measurements provides a very powerful means of assessing the SOC/SOH of lead acid batteries, including UPS cells. The fuzzy logic approach is robust, accurate, and reliable and may be implemented in a low cost microcontroller to provide a low cost battery monitoring system.

6.0 Acknowledgements

The authors gratefully acknowledge the assistance of Craig Fennie, Jr. in the fuzzy modeling of the defibrillator battery data and Yada Sangeetha Damodar for making the EIS measurements on the defibrillator batteries and Dr. Rodney LaFollette for making the EIS measurements on the VRLA batteries. The work on the portable defibrillator batteries was supported by a Phase I NIH STTR grant (Grant No. 1R41HL64984-01).

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