Fuzzy Logic-Based Determination of Pb-Acid Battery SOC by Impedance Interrogation Methods

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Abstract

Electrochemical impedance spectroscopy ("EIS") is a powerful tool for determining the physico-chemical properties of electrochemical devices, including both batteries and fuel cells. The implications of this approach to monitoring the on-board status of both energy storage and energy conversion devices in hybrid electric vehicles are clear. US Nanocorp and Villanova Univ. have co-developed a patented (1) fuzzy logic-based methodology to determine state-of-charge ("SOC") in batteries using a variety of interrogation probes, including coulomb counting, voltage delay and EIS (2, 3). By combining fuzzy logic and EIS at specific frequencies, a robust technique has been developed for determining SOC of Li/SO_2 and Li/MnO_2 primary cells (4). This technique has been extended to rechargeable batteries using spirally wound Pb-acid cells (2.5 Ah).

EIS data were taken after progressively discharging the Pb-acid cells in 10% intervals. A fuzzy logic model was developed to predict the cell SOC at different discharge rates. A second impedance approach for determining the SOC of cells is the Time Domain Spectroscopy ("TDS") method (5). In this approach a bipolar, square current pulse is applied to the cell and the time domain voltage response is monitored. TDS data has also been recorded on the same 2.5 Ah Pb-acid cell products. The TDS data was also taken in 10% discharge intervals. In this paper, the merits of each technique and the relative advantages/ disadvantages when combined with fuzzy logic analysis for determining the SOC of 2.5 Ah spirally wound Pb-acid cells are compared.

Introduction

Accurate SOC determination of batteries is essential for predicting the remaining distance that an electric vehicle may travel. Three basic interrogation methods exist for determining the SOC of a battery: 1) Coulomb counting, 2) voltage delay, and 3) impedance methods. Other methods, such as measuring electrolyte specific gravity are not practical for implementation in an electric vehicle fuel gauge/battery management system and are therefore not considered here. The coulomb counting method is the most widely used technique for battery fuel gauging in EVs. This method is reasonably accurate when SOC estimates are compensated for temperature and discharge rate variations. However, coulomb counting provides no diagnostic capability, which can be used to determine the state-of-health ("SOH") of batteries.

The voltage delay method is commonly used to perform battery tests outside a vehicle. In this case the battery is subjected to a transient load discharge and the voltage response of the battery monitored. The voltage recovery transient is then used to characterize the SOC of the battery. This technique is again limited in its ability to be implemented as an in-vehicle battery SOC/SOH instrument.

The third general class of methods is the application of a current/voltage excitation waveform to a battery and the monitoring of the battery's voltage/current response. In electrochemical impedance spectroscopy (EIS) the applied signal is a small amplitude, ac waveform so that the battery system is perturbed about its equilibrium condition. The frequency of the excitation waveform may be swept over a wide frequency range and the resultant battery response can be used to determine an equivalent circuit model of the battery and correlated with battery SOC. An alternative approach that we have developed is the determination of SOC by directly modeling the impedance response at a few discrete frequencies (using a fuzzy logic methodology) (4), without the intermediate step of extracting equivalent circuit models for the batteries. Impedance measurements have the distinct advantage of being rich with information related to the state-of-health of the battery and can therefore be useful in battery management systems for battery diagnostic purposes.

In time domain spectroscopy (TDS), the excitation waveform to the battery is a bipolar, square wave pulse stream. The voltage response of the battery is a series of transient responses in the time domain that change in shape and dc level as the battery is discharged.

In this paper we describe fuzzy logic analysis of both EIS and TDS data taken on 2.5 Ah spirally wound Pb-acid cells. Additionally, we compare the two techniques in terms of their abilities to produce useful equivalent circuit models for the Pb acid cell.

Review of 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".

Let us 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 us call this subset 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.

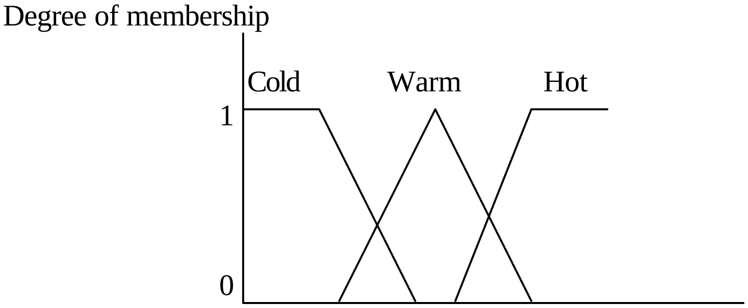

Fig. 1. Membership function for temperature

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 export 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 database that defines the membership functions for the input and output variables;
- A reasoning mechanism that performs the inference procedure, e.g. Mamdani or Sugeno;
- A defuzzification block that transforms the fuzzy output sets to a real valued output.

The rules relating the input and the 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.

Standard Additive Model (SAM)

While it is the *linguistic* view of FL that people are quick to cite and praise for its non-mathematical, almost intuitive structure, it is in fact the implementation of a FL model as an adaptive system that facilitates the construction of a FL model with sufficient accuracy necessary for function approximation such as SOC determination. A particular representation of a fuzzy system is known as the Standard Additive Model or SAM.

It will be helpful to start with a definition of terms.

IF-PART set-function factors refer to the input membership functions (mfs), while the joint IF-PART set function is the result of combining these factors with an "and" operation. Also since most FL systems have a single output variable, the THEN-PART set-functions are the output mfs.

Linguistically a simple-SAM FL system can be described as a set of n-rules of the form:

IF X is A_1, THEN Y is B_1.
.
IF X is A_n, THEN Y is B_n.

Where

- $X = \{x_1, x_2 \ldots x_r\}$, is a r-dimensional input vector,
- $Y = \{y_1, y_2 \ldots y_p\}$, is a p-dimensional output vector,
- A_j = j^{th} joint IF-PART set-function,
- B_j = j^{th} joint THEN-PART set-function.

In the SAM representation, THEN-PART set-functions, $B_j(Y)$, are scaled by the degree to which each rule "fires", $A_j(X)$, or

$$B_j^{'}(Y) = A_j(X)*B_j(Y).$$

Other methods of finding the fired THEN-PART set functions such as that used in traditional Mamdani reasoning, clip the output set-function by using the min function or $B_j^{'} = \min\{A_j(X), B_j(Y)\}$.

The SAM model is additive because it adds the fired THEN-PART set-functions to form the fired Output set-function, or

$$B(Y) = \sum_{j=1}^{n} w_j B_j^{'}(Y) = \sum_{j=1}^{n} w_j A_j(X) B_j(Y)$$

where w_j is the weight of the j^{th} rule, whereas in other schemes an "envelope" of the fired THEN-PART set-functions is obtained by taking the maximum of each fired set-function.

In particular, for a 2-input, 1-output system:

IF x_1 is a_1^1 *and* x_2 is a_1^2 THEN y is B_1
.
IF x_1 is a_n^1 *and* x_2 is a_n^2 THEN y is B_n.

Where

- x_1, x_2, and y are inputs 1 and 2 and the output respectively,
- a_n^1 and a_n^2 are the IF-PART set-function factors (or input mfs) of the n^{th} rule,
- B_n is the THEN-PART set-function (or output mfs) of the n^{th} rule.

The IF-PART set-function factors, a_j^1 and a_j^2, are typically combined to find the joint IF-PART set-function, A_j, by two methods:

$$A_j(X) = \min\{a_j^1(x_1), a_j^2(x_2)\ldots a_j^r(x_r)\}, \qquad \text{the min-combiner,}$$

and

$$A_j(X) = a_j^1(x_1)*a_j^2(x_2)\ldots *a_j^r(x_r), \qquad \text{the product-combiner.}$$

Either method may be employed in the SAM model but it is thought that the product-combiner should lend itself to a more efficient model than the min-combiner.

Finally the simple-SAM model uses Centroid Defuzzification to find the scalar output, F(X):

$$F(X) = \text{Centroid}\{B\}$$

$$F(x) = \frac{\sum_{j=1}^{n} w_j A_j(x) V_j c_j}{\sum_{j=1}^{n} w_j A_j(x) V_j}$$

with V_j and c_j as the volume and centroid of the j^{th} THEN-PART set-function respectively.

It is important to note that once the model is found, the weights, volumes, and centroids are known. The only parameter that needs to be calculated for each new input is the "fit" value $a_j = A_j(x)$ for a particular input. This allows for relatively straightforward hardware implementation. Also, clustering algorithms may be used to find the IF-PART set-function factors while gradient descent based algorithms may be used to "tune" the volume and centroids of the THEN-PART set-functions.

In the simple SAM model, it has been assumed that the THEN-PART set functions, $B_j(Y)$, do not depend on the input, X. These set-functions are then analogous to output mfs that define subsets of the output set Y. This is reminiscent of the generalized Mamdani or reasoning-with-sets approach to FL. It can be shown that the SAM model can be generalized to include THEN-PART set functions that do depend on the inputs, or $B_j(Y,X)$. Therefore

$$B(Y,X) = \sum_{j=1}^{n} w_j B_j^{'}(Y,X) = \sum_{j=1}^{n} w_j A_j(X) B_j(Y,X)$$

If $B_j(Y,X) = \delta(Y-B_j(X))$, where $\delta(Y)$ is the Dirac delta function, and $B_j(X) = b_1^0 + x_1 b_1^1 + x_2 b_1^2$, where x_1 and x_2 are the inputs and b_1^0, b_1^1, and b_1^2 are constants, then the so-called generalized SAM model is analogous to the Sugeno approach to FL. The reader is referred to the monograph by Kosko (6) for details for the SAM approach to Fuzzy Logic.

EIS and TDS measurements

Electrochemical Impedance Spectroscopy (EIS) and time domain spectroscopy (TDS) data have been collected on Hawker 2.5 Ah, “D"-size Pb-acid cells. The EIS data was collected using both a Solartron 1250 Frequency Response Analyzer (“FRA”) with a PAR 273 Potentiostat /Galvanostat and a Solartron 1280b over the frequency range of 1.0 Hz – 65 kHz while the TDS data was taken using the Solartron 1280b. In the case of the EIS data, the commercial software programs Zplot and Corrware (Scribner Associates) were used to collect and analyze the data. The TDS measurements used the galvanic square-wave routine in Corrware.

The EIS and TDS data were collected following an identical test procedure. An initialization procedure consisting of 5 charge/discharge cycles was performed on each new cell. After completion of this initialization, EIS/TDS data were collected at various states-of-charge (SOCs) on three different discharge cycles for each cell. 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 or TDS measurement.
5) Repeat steps 2-4 until end-of-discharge reached (1.69 V).

All EIS measurements have been performed in potentiostatic mode whereby a 10 mV sinusoidal voltage signal is applied to the cell and the resultant current is measured. All TDS measurements have been performed by applying a bipolar square-wave with amplitude C/2.

Pre-Processing of EIS and TDS data

In the case of the EIS data, we have preprocessed the acquired data into a form that makes it easily amenable to fuzzy logic modeling. This involved finding one or more frequencies where the variation in the magnitude and/or phase angle of the impedance can provide satisfactory discrimination between successive SOC values. The impedance at these frequencies does not have to vary monotonically (or at all) over the entire range of SOC. A key attribute of the FL approach is in combining several measures of SOC, each containing partial information. Once these frequencies are found, the impedance at these frequencies can be readily available as inputs to the FL model. Figs. 2 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.

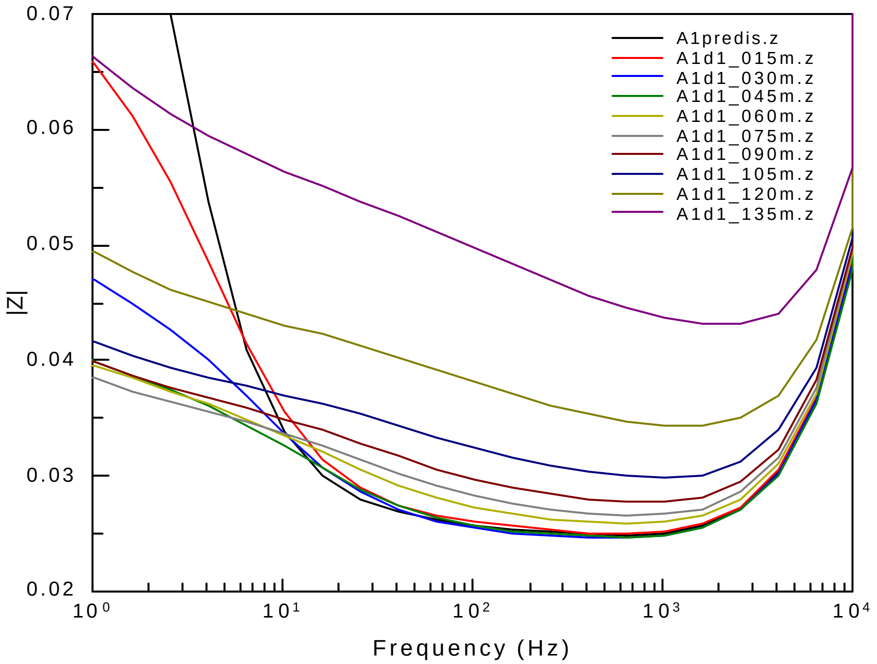

Fig. 2a. Magnitude of the Impedance |Z| *vs.* frequency at various SOCs (Hawker Pb-acid, 2.5 Ah "D"-size cell). Note: predis is 100% SOC, _135m is 0 % SOC.

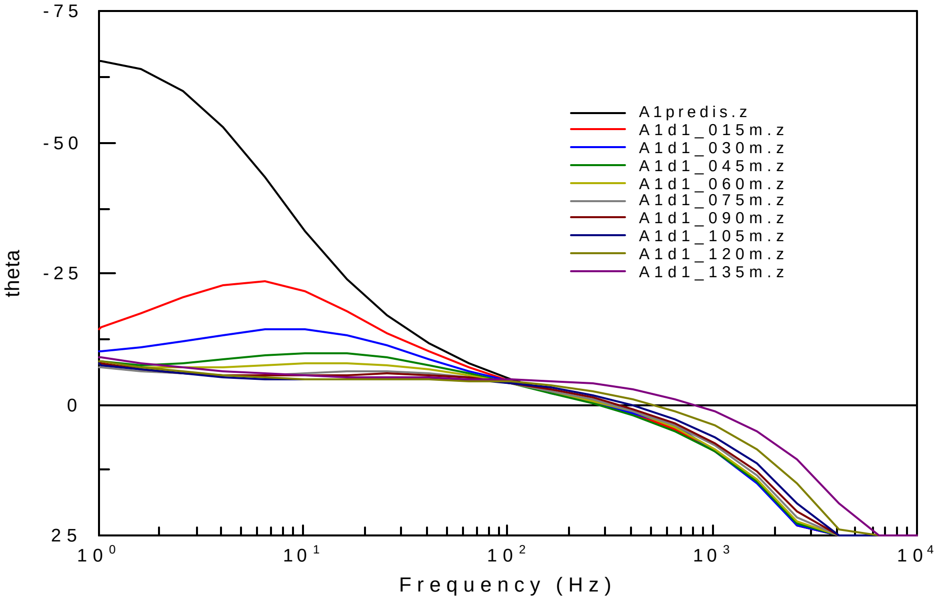

Fig. 2b. Phase Angle of the Impedance *vs*. frequency at various SOCs (Hawker Pb-acid, 2.5 Ah "D"-size cell). Note: predis is 100% SOC, _135m is 0 % SOC.

Acquired TDS data has been reduced to a form readily accessible to a fuzzy logic model. As an initial pre-process step, one TDS cycle has been captured and displayed as a function of SOC for Cell – 'm22' and Cell-'m24' in Figs. 3 a-b respectively. To further reduce the TDS waveform, certain features are shown to vary with SOC. Preliminary data analysis suggests that three features of the TDS waveform vary significantly with SOC. These features, shown in Figs. 7 a-c as a function of SOC, are:

1) Mean Voltage of one TDS cycle.
2) Maximum Voltage of one TDS cycle minus the Mean Voltage.
3) Minimum Voltage of one TDS cycle minus the Mean Voltage.

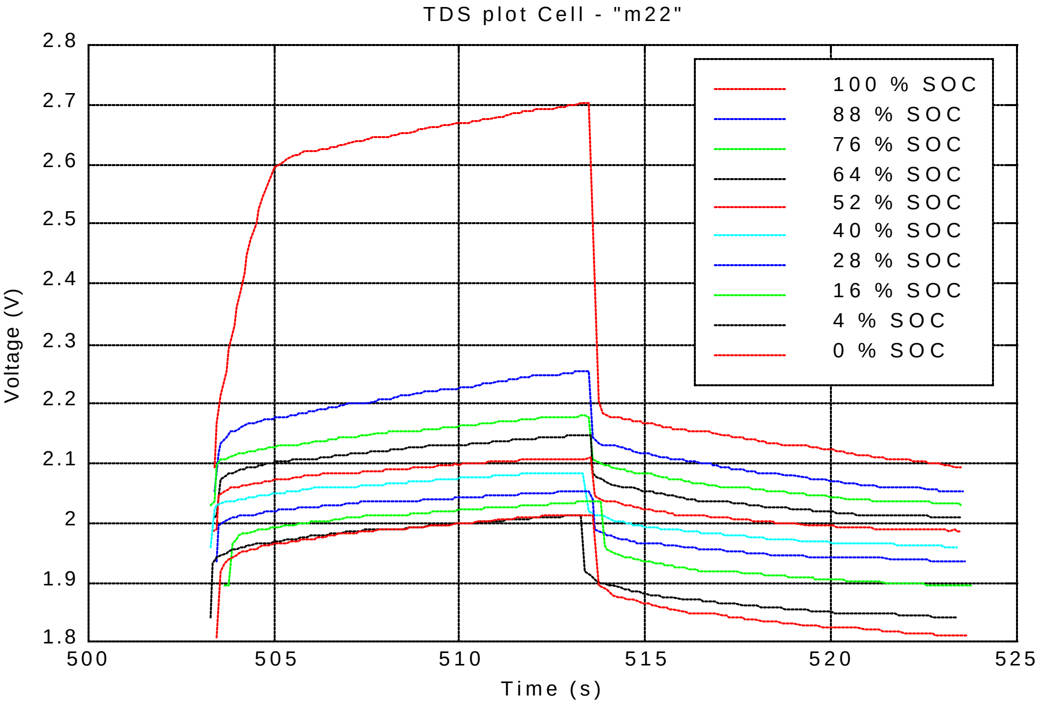

Fig. 3a. Time Domain Spectroscopy (TDS) Voltage vs. time at various SOCs (one cycle) Hawker Pb-acid, 2.5 Ah "D"-size cell, Cell - 'm22'

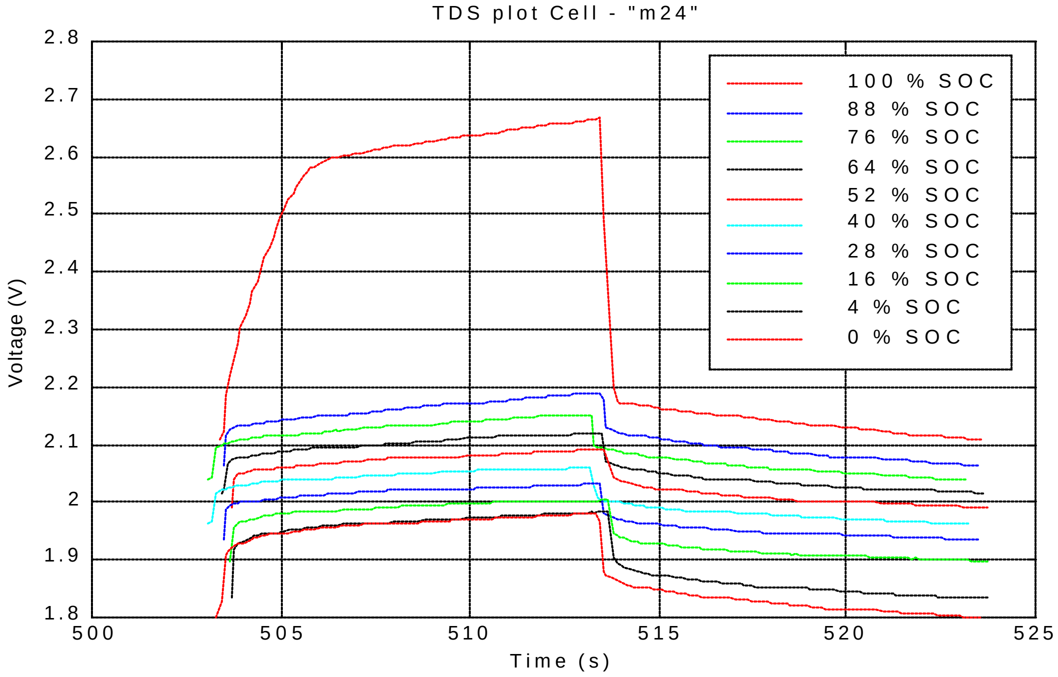

Fig. 3b. Time Domain Spectroscopy (TDS) Voltage vs. time at various SOCs (one cycle) Hawker Pb-acid, 2.5 Ah "D"-size cell, Cell - 'm24'

Fuzzy Logic Modeling of EIS data

A Fuzzy Logic model was developed using MATLAB®, a mathematical software package, and the Fuzzy Logic Toolbox for MATLAB®. A 3-input, 1-output model was developed, using Standard Additive Model. A "training" data set was developed using the EIS data of Cell 'A' (Figs. 4a-c). Clustering algorithms were used to find the initial IF-PART set function factors, or input membership functions (Fig. 5 a-c), the centroids of the THEN-PART set functions or output membership functions(volumes initially set equal to 1) and the rules. Fine-tuning of the rules was performed by using gradient descent based learning algorithms to adaptively estimate the volumes and centroids of the THEN-PART membership functions. The optimized rules are shown in Table 1. Finally, the model was tested using undocumented cells, Cell 'B', 'C', 'm22', and 'm24'. The capacity of Cell 'B' was ~ 78 % that of 'A' while the capacity of cell 'C', 'm22', and 'm24' was similar to the training-set cell 'A'. As shown in Figs. 6 a-d, the model predicts the SOC of undocumented cells (i.e. ones for which the FL model had no prior knowledge of these cells' behavior) to within ~ 5%, which is especially good for Cell B considering its capacity was 22% less than the cell that was used for the model development.

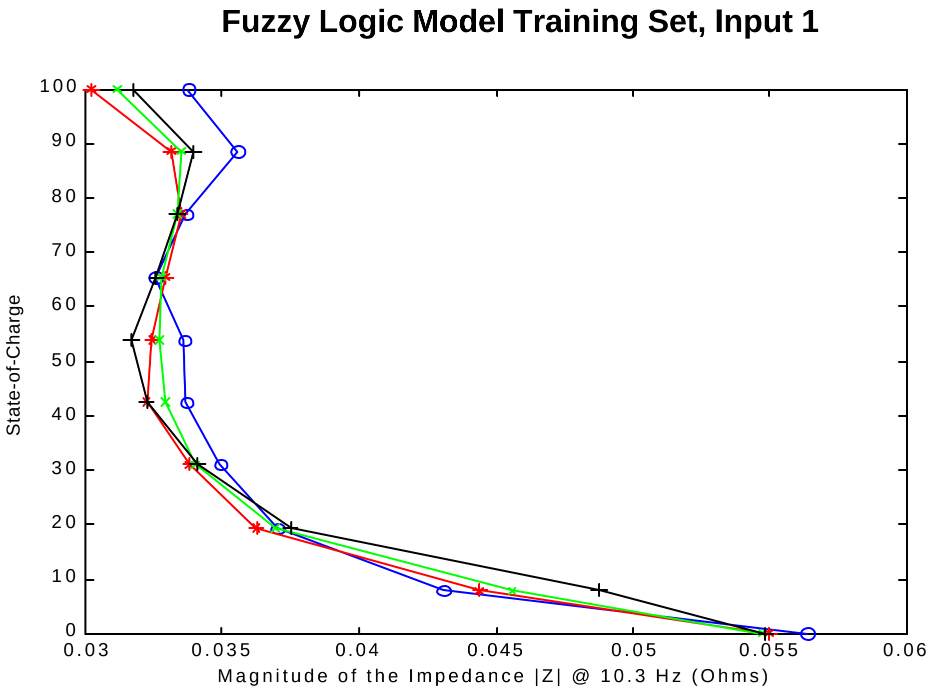

Fig. 4a Magnitude of Impedance @ 10.3 Hz vs. State-of- Charge (Hawker Pb-acid, 2.5 Ah, "D"- size). Each line corresponds to a different discharge cycle for a particular cell.

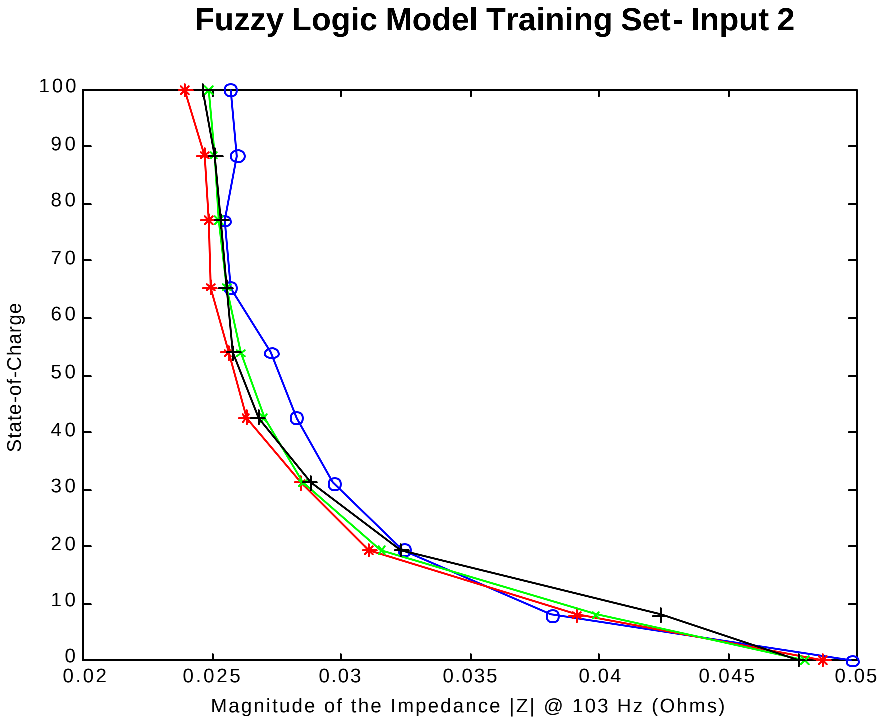

Fig. 4b Magnitude of Impedance @ 103 Hz *vs.* State-of-Charge (Hawker Pb-acid, 2.5 Ah, "D"- size). Each line corresponds to a different discharge cycle for a particular cell.

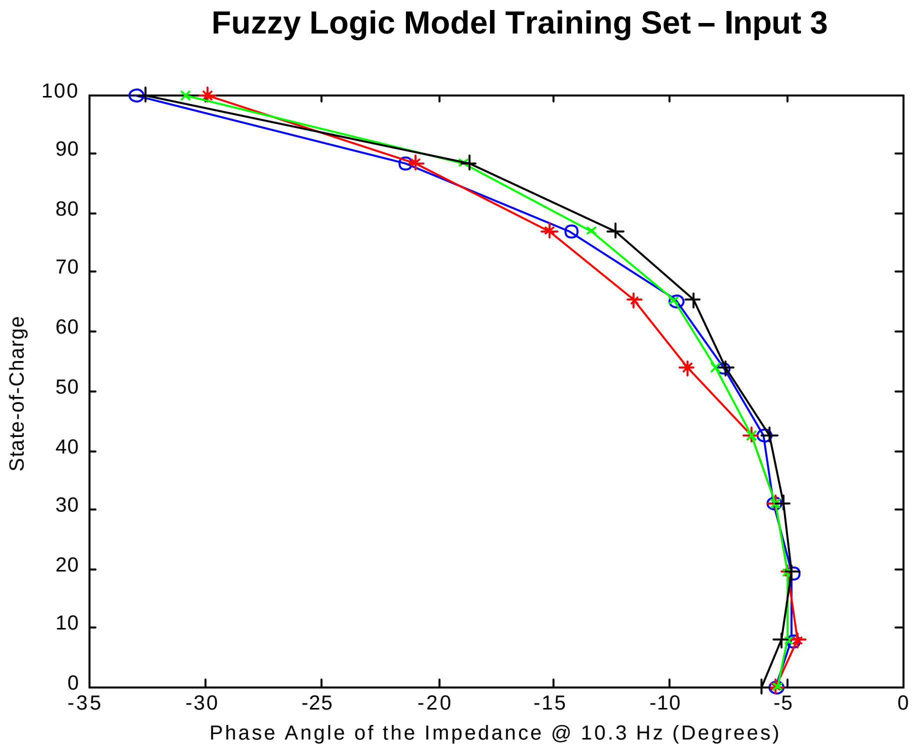

Fig. 4c Phase Angle of Impedance @ 10.3 Hz vs. State-of- Charge (Hawker Pb-acid, 2.5 Ah, "D"- size). Each line corresponds to a different discharge cycle for a particular cell.

Table 1. SAM - Fuzzy Logic SOC Model Rules – EIS

1. **If** (in1 is in1mf1) *and* (in2 is in2mf1) *and* (in3 is in3mf1) **then** (SOC is 54.0) (1)
2. **If** (in1 is in1mf2) *and* (in2 is in2mf2) *and* (in3 is in3mf2) **then** (SOC is 31.0) (1)
3. **If** (in1 is in1mf3) *and* (in2 is in2mf3) *and* (in3 is in3mf3) **then** (SOC is 77.0) (1)
4. **If** (in1 is in1mf4) *and* (in2 is in2mf4) *and* (in3 is in3mf4) **then** (SOC is 19.5) (1)
5. **If** (in1 is in1mf5) *and* (in2 is in2mf5) *and* (in3 is in3mf5) **then** (SOC is 00.0) (1)
6. **If** (in1 is in1mf6) *and* (in2 is in2mf1) *and* (in3 is in3mf1) **then** (SOC is 88.5) (1)
7. **If** (in1 is in1mf7) *and* (in2 is in2mf2) *and* (in3 is in3mf2) **then** (SOC is 100.0) (1)
8. **If** (in1 is in1mf8) *and* (in2 is in2mf3) *and* (in3 is in3mf3) **then** (SOC is 08.0) (1)
9. **If** (in1 is in1mf9) *and* (in2 is in2mf4) *and* (in3 is in3mf4) **then** (SOC is 65.5) (1)
10. **If** (in1 is in1mf10) *and* (in2 is in2mf5) *and* (in3 is in3mf5) **then** (SOC is 42.5) (1)
11. **If** (in1 is in1mf10) *and* (in2 is in2mf5) *and* (in3 is in3mf5) **then** (SOC is 08.0) (1)

where input1 is |Z| @ 10.3 Hz
input2 is |Z| @ 103 Hz
input3 is θ @ 10.3 Hz

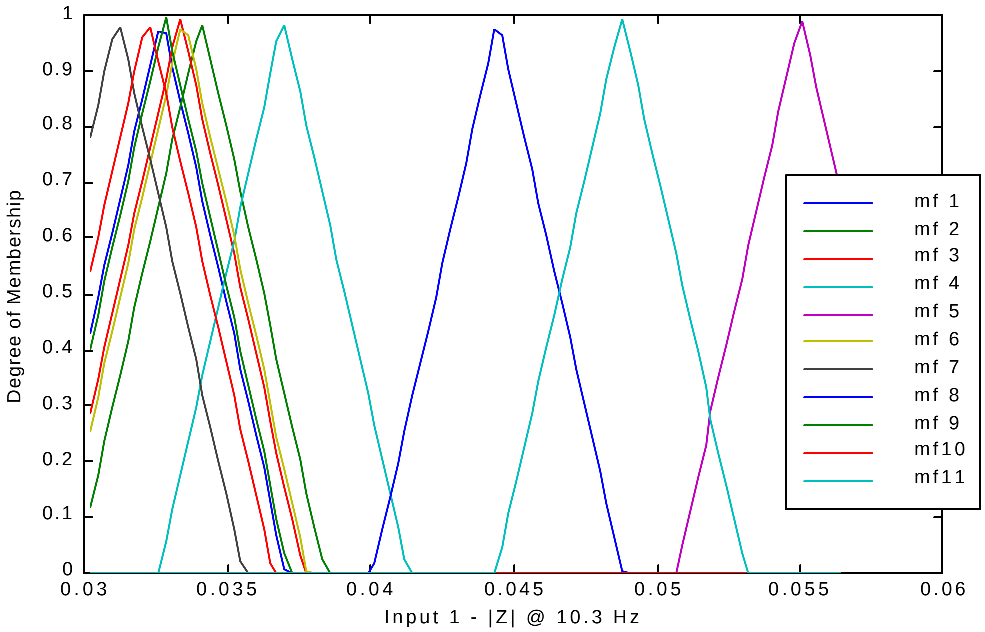

Fig. 5a. SAM - Fuzzy Logic Model Membership Functions (EIS), Input 1 Magnitude of Impedance (ohms) @ 10.3 Hz Hawker Pb-acid, 2.5 Ah, "D"-size.

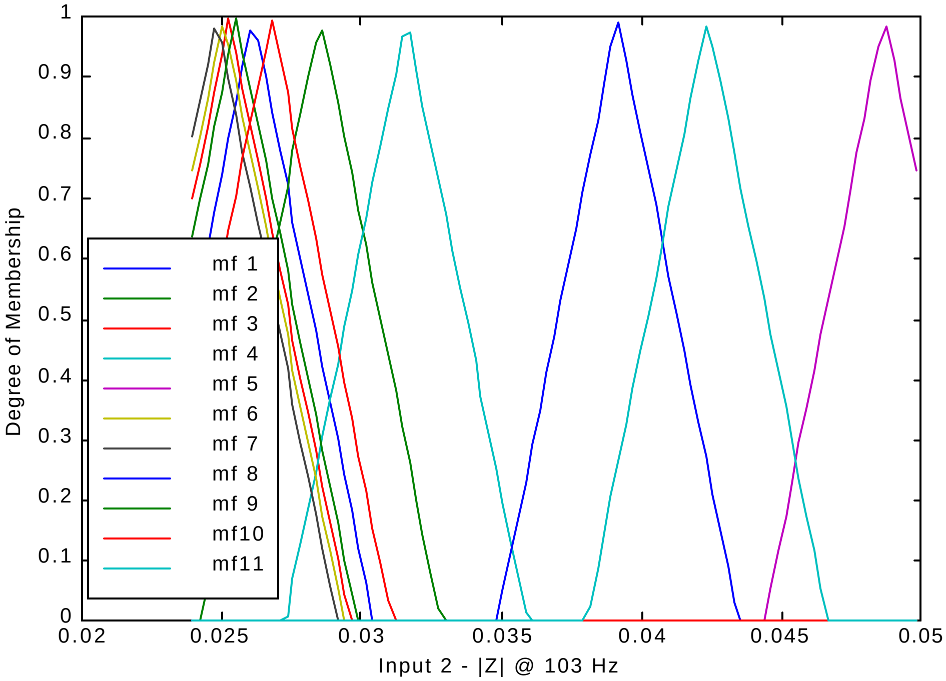

Fig. 5b. SAM - Fuzzy Logic Model Membership Functions (EIS), Input 2 Magnitude of Impedance (ohms) @ 103 Hz Hawker Pb-acid, 2.5 Ah, "D"-size.

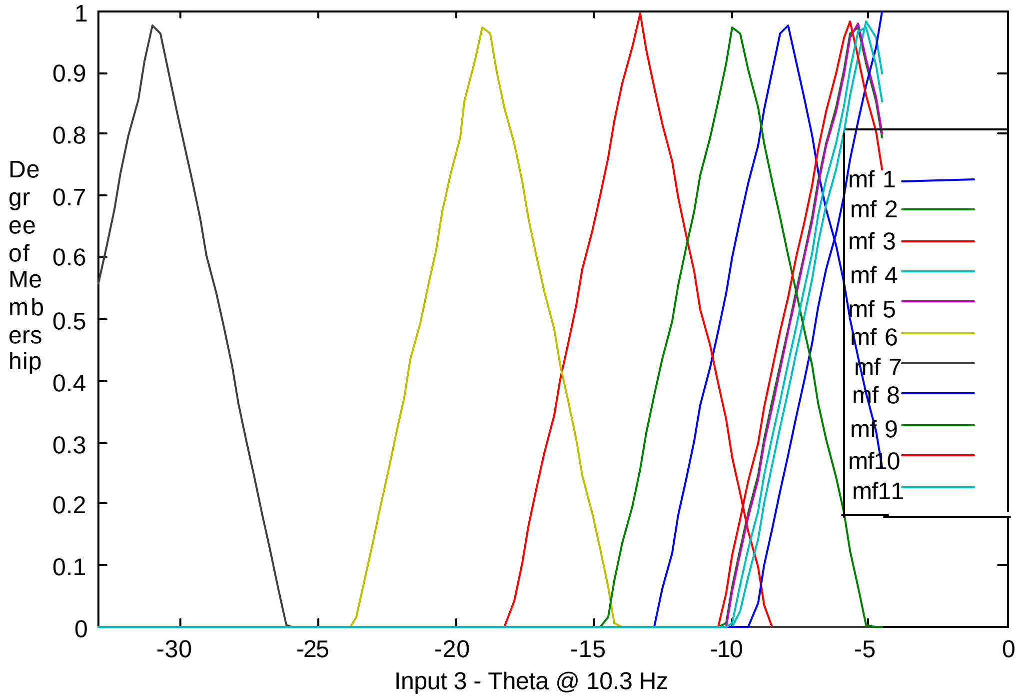

Fig. 5c. SAM - FL Model Membership Functions (EIS), Input 3 Phase Angle of Impedance @ 10.3 Hz, Hawker Pb-acid, 2.5 Ah, "D"-size .

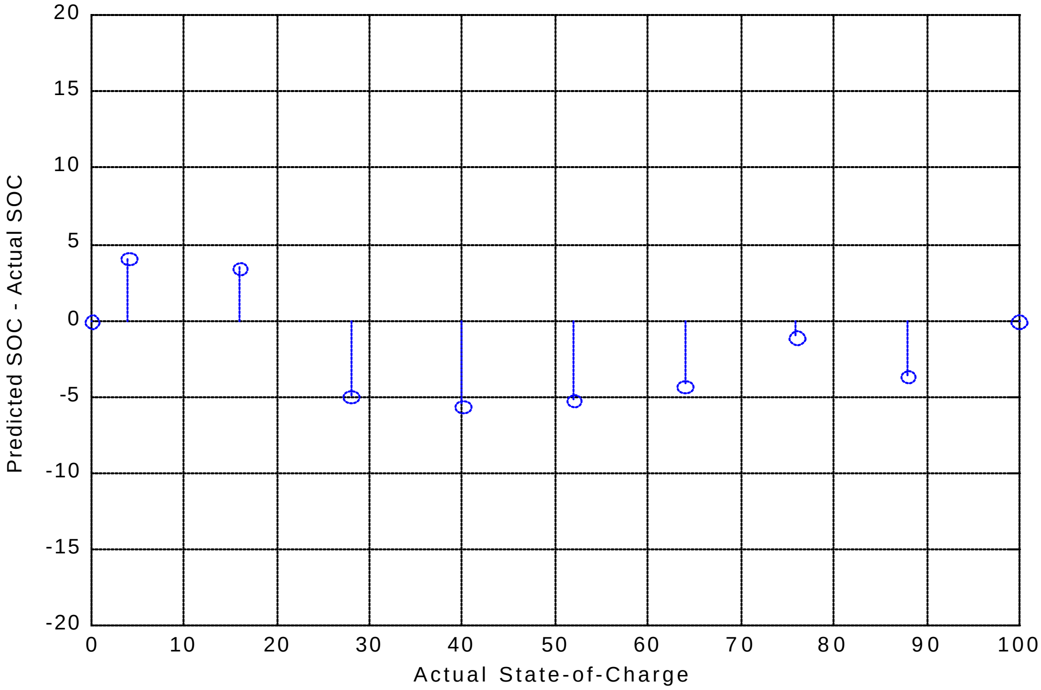

Fig. 6a. SAM - FL Model Predicted SOC vs. Actual (EIS). Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell – 'm22'. RMS Error = 3.8079

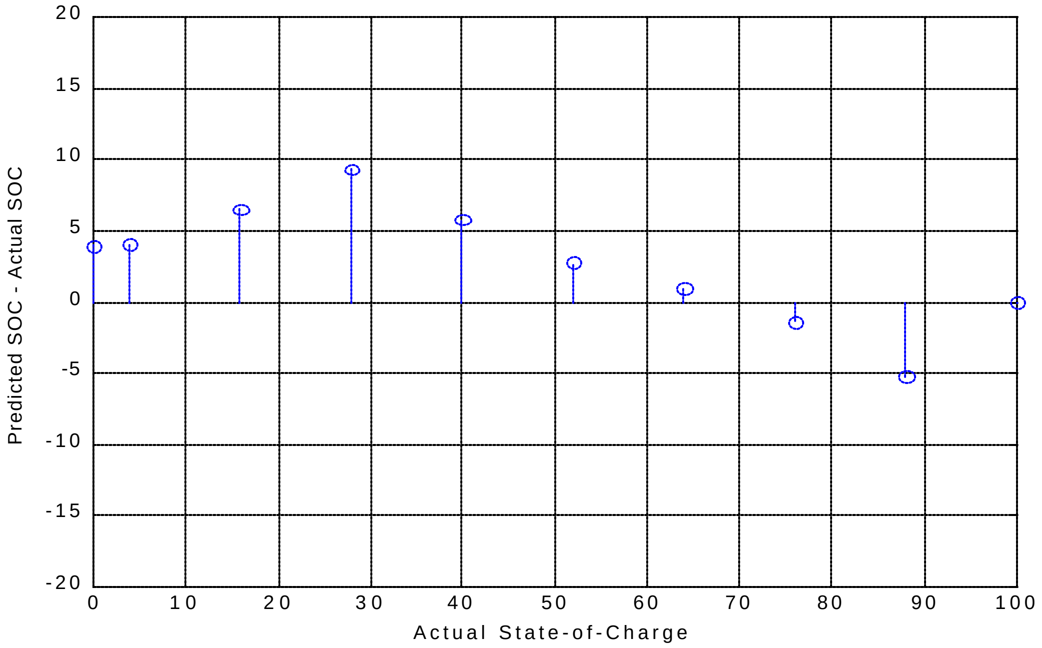

Fig. 6b. SAM - FL Model Predicted SOC vs. Actual (EIS). Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell - 'm24'. RMS Error = 4.8151

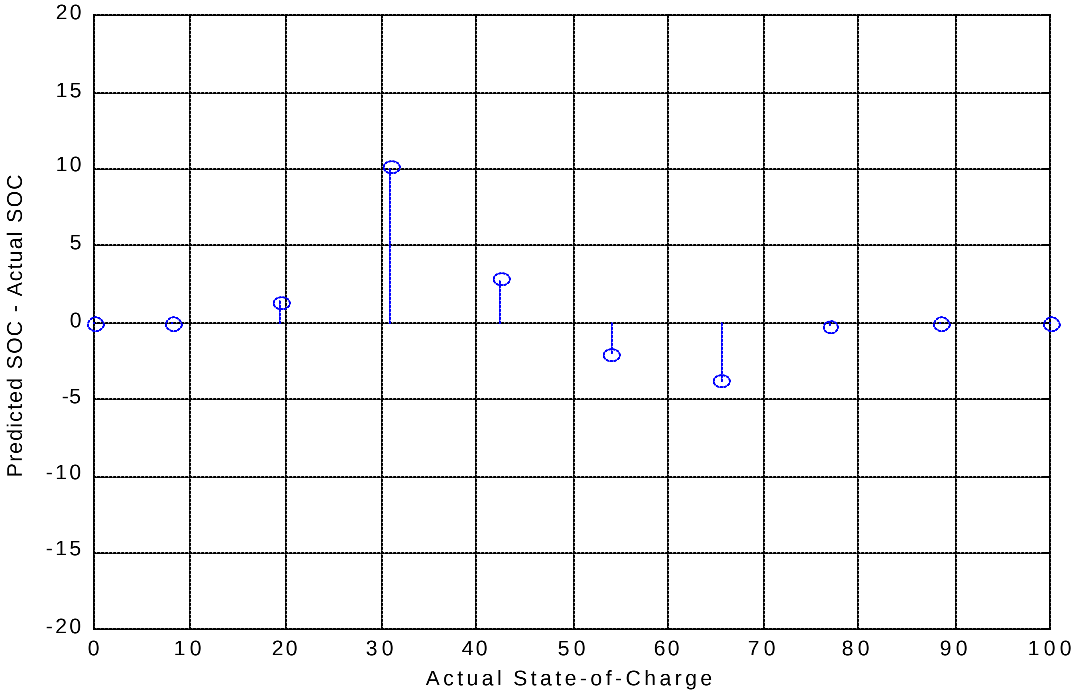

Fig. 6c. SAM - FL Model Predicted SOC vs. Actual (EIS). Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell - 'C'. RMS Error = 3.6204

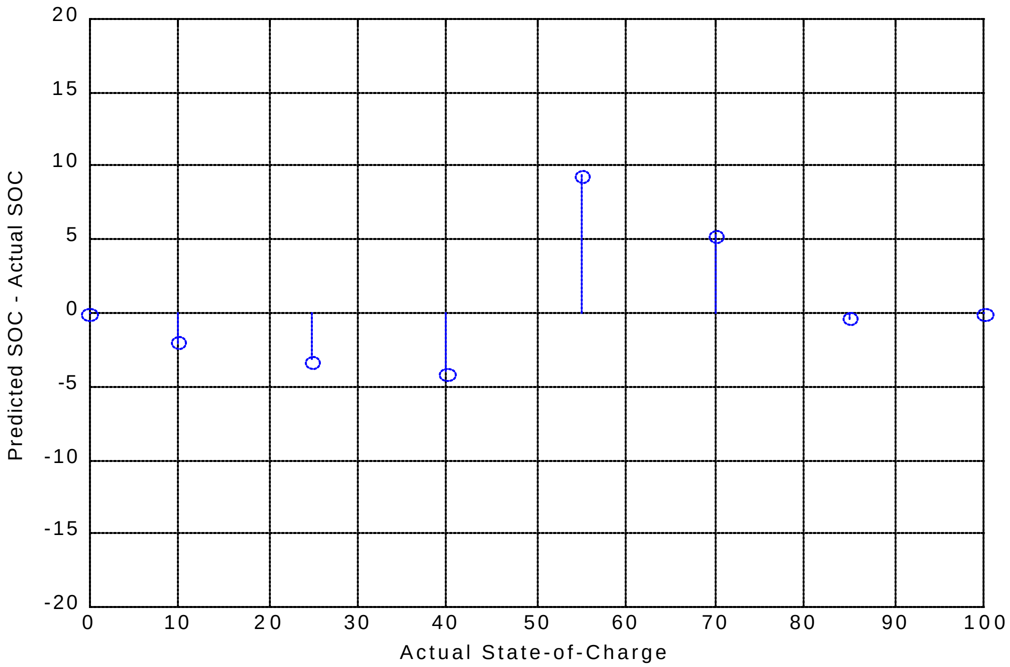

Fig. 6d. SAM - FL Model Predicted SOC vs. Actual (EIS). Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell - 'B'. RMS Error = 4.2618

Fuzzy Logic Modeling of TDS data

As previously stated three features of the TDS waveform vary significantly with SOC, Figs. 7 a-c. Although the features identified as the Max-Mean Voltage and Mean-Min Voltage do vary with SOC, an initial FL model based on just the Mean Voltage of one TDS cycle has been developed.

Models were developed using MATLAB® and the Fuzzy Logic (FL) Toolbox for MATLAB®. An initial model consists of a 1-input, 1-output system developed using custom algorithms to implement the Standard Additive Model (SAM) Inference method where input 1 is the Mean Voltage over one TDS cycle and the output is the SOC. The data from cell 'm22' was used to construct the model. The rules found are shown in Table 2 while the membership functions are shown in Fig. 8.

The model was tested using undocumented data from Cell-'m24'. The results are shown in Fig. 9.

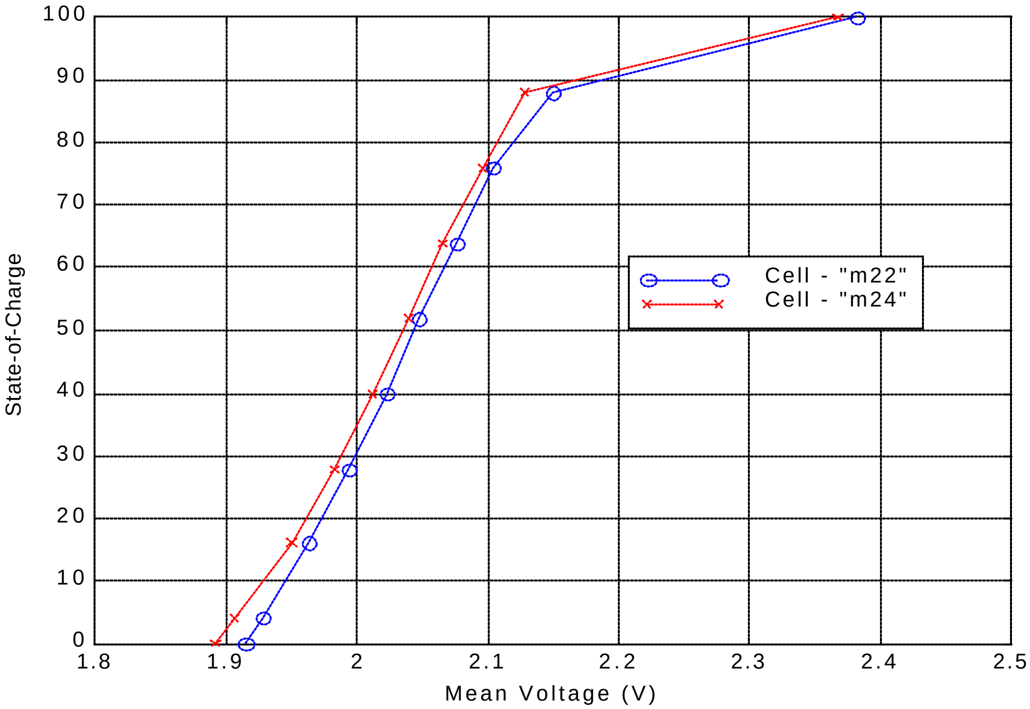

Fig. 7a. Fuzzy Logic SOC Model Data Set (TDS), Input 1. Mean Voltage (one cycle) vs. SOC Hawker Pb-acid, 2.5 Ah, "D"-size.

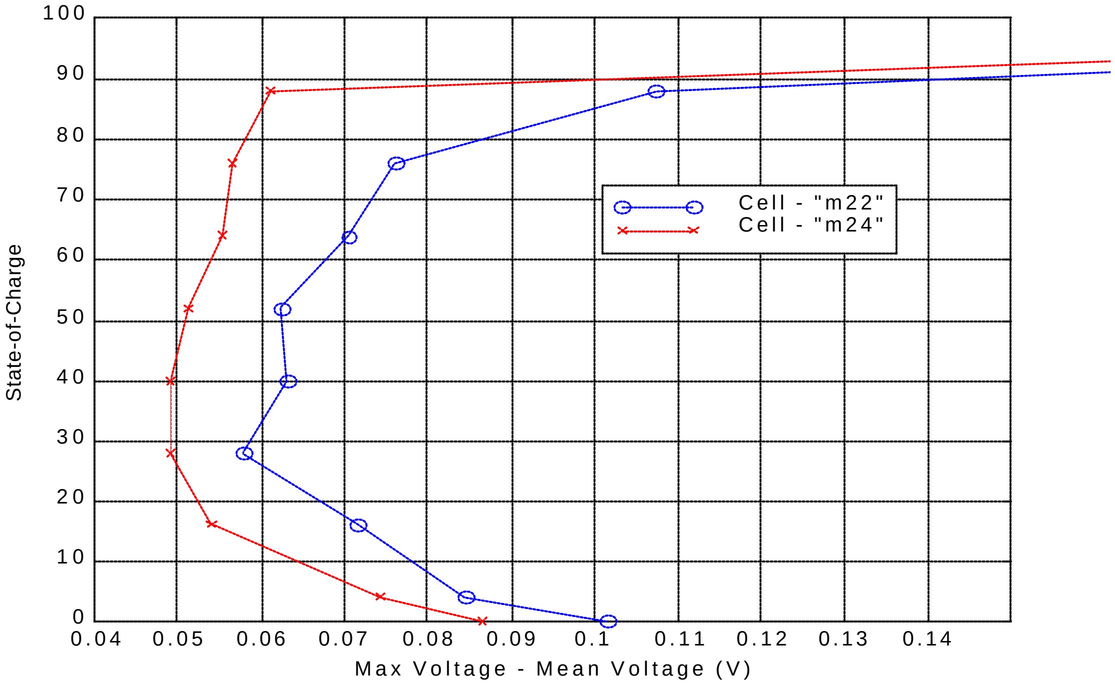

Fig. 7b. Fuzzy Logic SOC Model Data Set (TDS), Input 2. (Max Voltage - Mean Voltage) (one cycle) vs. SOC Hawker Pb-acid, 2.5 Ah, "D"-size.

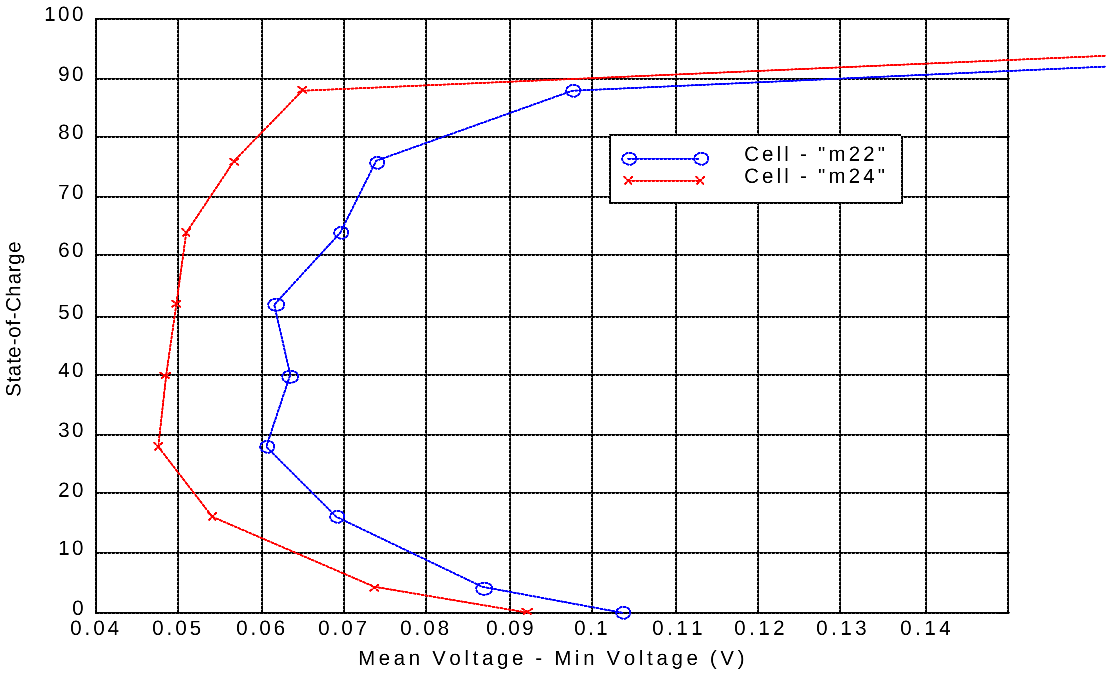

Fig. 7c. Fuzzy Logic SOC Model Data Set-TDS, Input 3. (Mean Voltage - Min Voltage) (one cycle) vs. State-of-Charge Hawker Pb-acid, 2.5 Ah, "D"-size.

Table 2. SAM - Fuzzy Logic SOC Model Rules – TDS

1. If (in1 is in1mf1) then (SOC is 04.0) (1)
2. If (in1 is in1mf2) then (SOC is 40.0) (1)
3. If (in1 is in1mf3) then (SOC is 64.0) (1)
4. If (in1 is in1mf4) then (SOC is 88) (1)
5. If (in1 is in1mf4) then (SOC is 100.0) (1)

where input1 is Mean Voltage

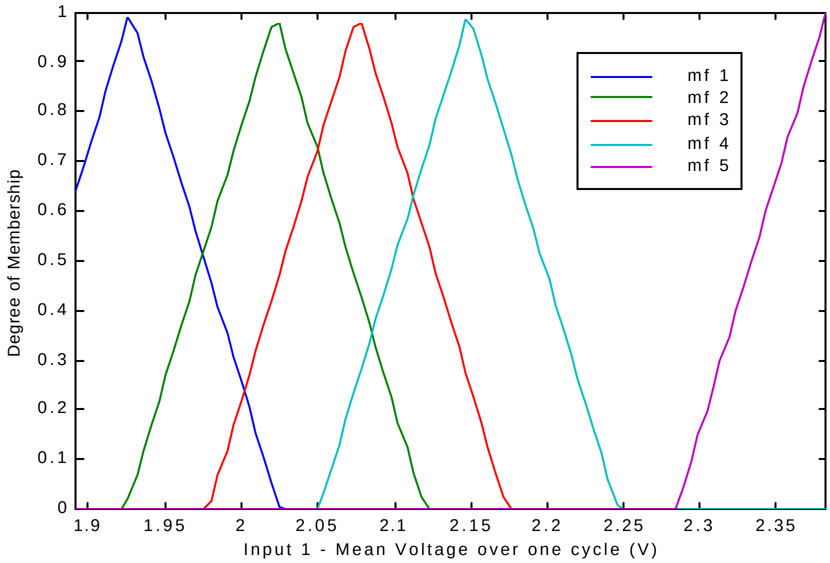

Fig. 8. SAM - FL Model Membership Functions (TDS), Input 1. Mean Voltage (V) over one TDS cycle Hawker Pb-acid, 2.5 Ah, "D"-size.

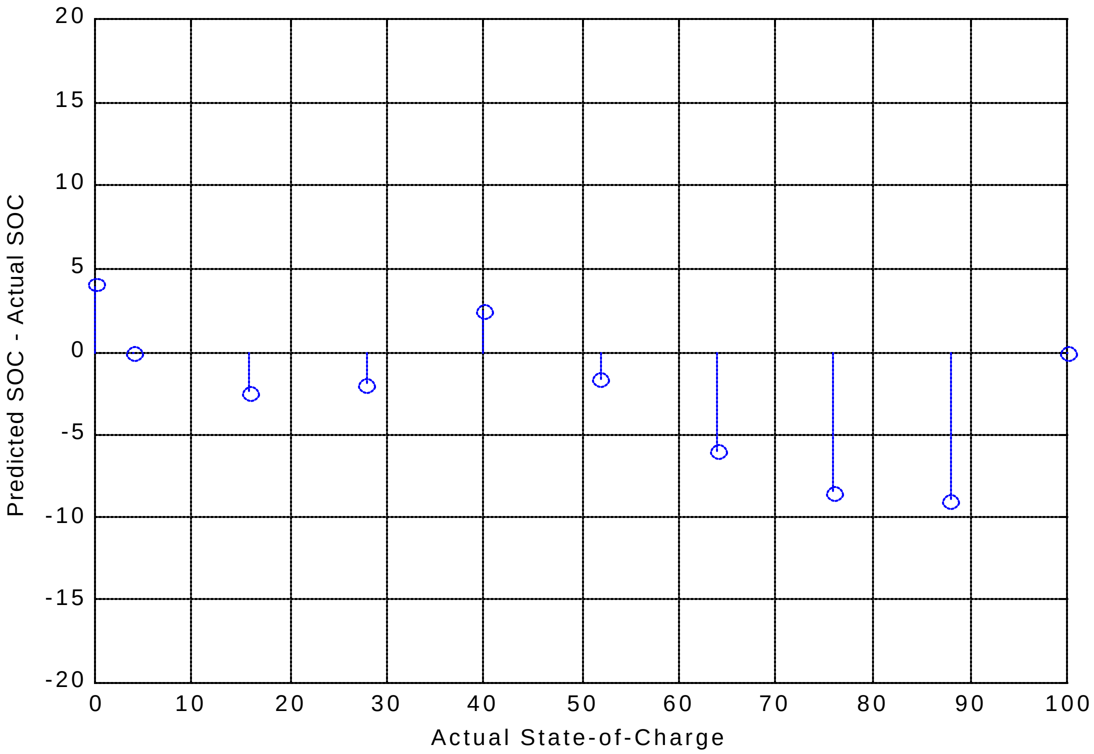

Fig. 9. SAM - FL Model Predicted SOC vs. Actual (TDS) Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell - 'm24'. RMS Error = 4.7328

Conclusions

We have applied EIS and TDS methods on Hawker Pb-acid, 2.5 Ah, "D"-size cells at various SOCs. These data sets have been preprocessed so as to be readily accessible to fuzzy logic modeling. In the case of EIS, a subset of the acquired data was used to develop a preliminary 3-input, 1-output FL model, based on the relationship between the impedance and SOC of ONE particular cell. The developed FL model has been used to predict the SOC of four undocumented cells within approximately 5 % of actual SOC predicted by back calculating. *It is particularly noteworthy that the FL model was able to accurately predict the SOC of the undocumented cell "B", whose actual capacity was ~ 25 % less than that of the cell used to develop the model.*

In the case of TDS, a subset of the acquired data was used to develop a preliminary 1-input, 1-output FL model, based on the relationship between the mean voltage over one TDS cycle and SOC of ONE particular cell. The developed FL model has been used to predict the SOC of one undocumented test cell within approximately 5% of actual SOC predicted by back calculating.

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