Development of Fuzzy Logic-Based Lead Acid Battery Management Techniques with Applications to 42V Systems

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Abstract

As the implementation of 42 volt systems is being phased into commercial vehicles, the battery technology is being developed with little time for adequate long-term testing and modeling to assess battery performance before their implementation into vehicles. This makes the development of battery monitoring and management systems for these 42 volt systems critical for long-term reliability. Furthermore, these battery monitoring and management systems must be developed rapidly and be adaptable to the changing characteristics of the batteries as they age.

Over the last five years, Villanova University and US Nanocorp have been jointly developing patented fuzzy logic-based technology [1-3] for estimating the state-of-charge (SOC) and state-of-health (SOH) of batteries. This methodology has proven to be both a simple and a powerful means to model battery characteristics accurately and robustly. The methodology can be interfaced to any battery interrogation technique including coulomb counting, voltage recovery, and battery impedance methods. Furthermore, the use of neural network-based algorithms can be used to adaptively modify the fuzzy algorithms based on changing battery conditions. Finally, the fuzzy logic methodology lends itself well to rapid system design and development, and can be implemented efficiently in existing on-board vehicle microprocessors.

In this paper, we will describe how impedance measurements and voltage response measurements combined with fuzzy logic data analysis have been used to estimate the SOC of spirally wound 2V lead acid cells. We will also describe how this approach may be extended to 42V battery systems.

Introduction

As the implementation of 42 volt systems is being phased into commercial vehicles, the battery technology is being developed with little time for adequate long-term testing and modeling to assess battery performance before their implementation into vehicles. This makes the development of battery monitoring and management systems for these 42 volt systems critical for long-term battery reliability. Furthermore, these battery monitoring and management systems must be developed rapidly and be adaptable to the changing characteristics of the batteries as they age.

Three basic methods exist for determining the state-of-charge (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 a 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 various applications including laptop computers and electric vehicles [4,5]. This method is reasonably accurate when SOC estimates are compensated for temperature and discharge rate variations. However, coulomb counting provides no diagnostic for determining 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 [6]. 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 parameters of which may be correlated with battery SOC [7]. 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), 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 SOH of the battery and can therefore be useful in battery management systems for battery diagnostic purposes.

Another approach that we have investigated is sometimes referred to as time domain spectroscopy (TDS). In this method, 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 how the fuzzy logic data analysis technique can be combined with either EIS or TDS data taken on Hawker 2.5Ahr spiral wound lead acid cells to determine the battery’s SOC. Additionally, we describe how this same technique may be extended to estimating the SOC/SOH of 42 volt battery systems.

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. Figure 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.

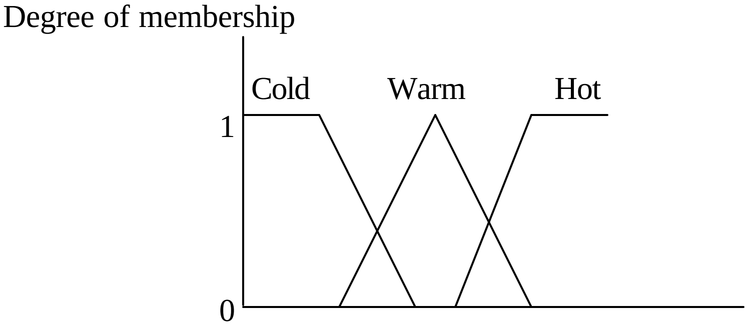


Fig. 1. Membership function for temperature

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 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 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 [8].

EIS and TDS measurements

Electrochemical Impedance Spectroscopy (EIS) and time domain spectroscopy (TDS) data have been collected on Hawker 2.5 Ah,“D"-size Lead Acid cells. The EIS data was collected using a Solartron 1250 Frequency Response Analyzer (FRA) and a PAR 273 Potentiostat /Galvanostat over the frequency range of 1.0 Hz – 65 kHz while the TDS data was taken with a Solartron 1280B combined potentiostat/galvanostat and FRA. The commercial software programs Zplot and Corrware (Scribner Associates) were used to collect and analyze the data [9].

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 – 65kHz.
2) Galvanostatic discharge at 1 A for 15 mins.
3) Rest at open circuit for 1 min.
4) EIS 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. Figs. 2a-b show the magnitude and phase angle, respectively, of the impedance *vs*. frequency for a typical cell at various SOCs.

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. 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. 3 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.

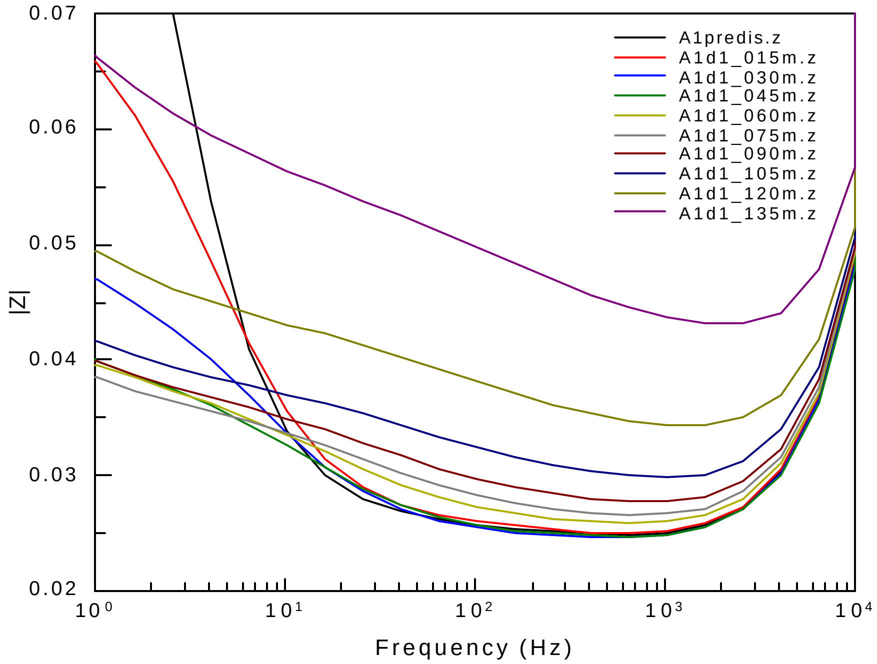


Fig.2a Magnitude of the Impedance |Z| *vs*. frequency at various SOCs (Hawker Pb-Acid, 2.5 Ah "D"-size cell). Note: predis is 100% SOC, _135m is 0 % SOC.

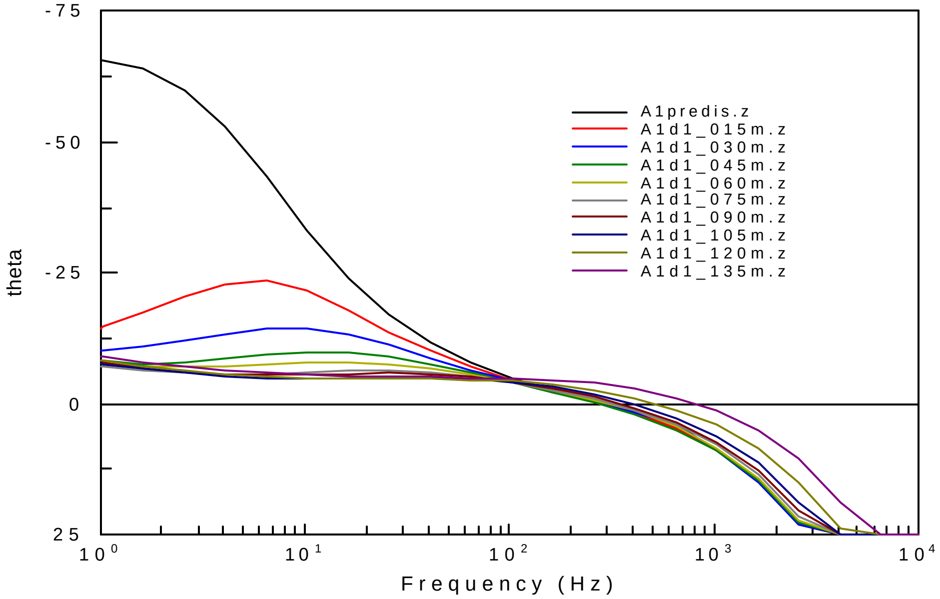


Fig. 2b Phase Angle of the Impedance *vs*. frequency at various SOCs (Hawker Lead Acid, 2.5 Ah “D"-size cell). Note: predis is 100% SOC, _135m is 0 % SOC.

Acquired TDS data were reduced to a form readily accessible to a fuzzy logic model. Preliminary analysis of data such as that of Fig. 3, suggested that three features of the TDS waveform varied significantly with SOC.

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.

These three factors served as the input parameters for the fuzzy logic model and the battery SOC was the output of the model.

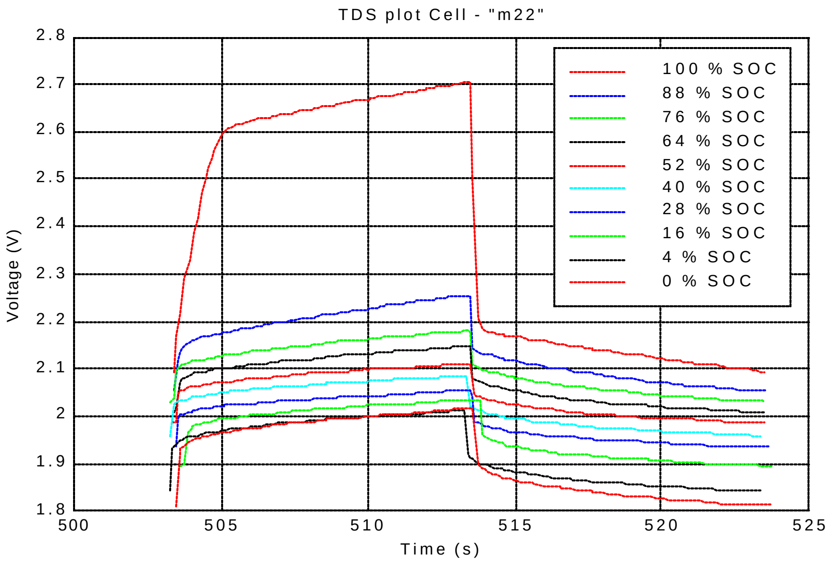


Fig. 3. Time Domain Spectroscopy (TDS) Voltage vs. time at various SOCs (one cycle) Hawker Pb-acid, 2.5 Ah "D"-size cell, Cell - 'm22'

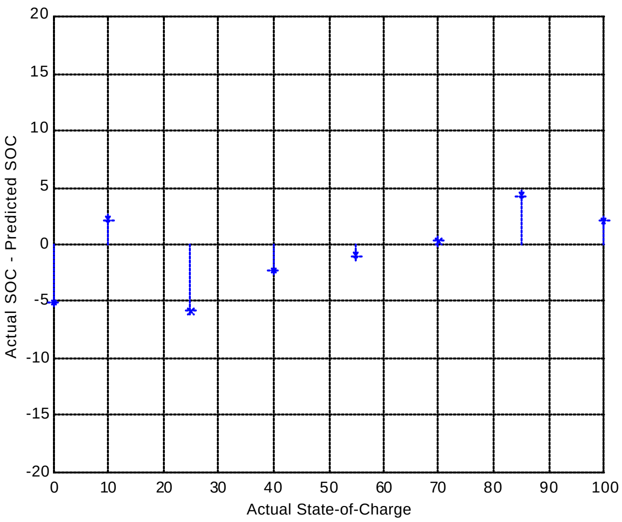
Fuzzy Logic Modeling of EIS data

A Fuzzy Logic model was developed using MATLAB, a mathematical software package, and the Fuzzy Logic Toolbox for MATLAB [10]. A 3-input, 1-output model was developed, using a Sugeno Inference approach. A "training" data set was developed using the EIS data of Cell 'A'. Clustering algorithms were used to find initial membership functions and rules (the rules are presented in Table 1). Fine tuning of the rules was performed by incorporating our expert knowledge into the model. Finally, the model was tested using undocumented cells, Cell 'B' and Cell 'C'. The capacity of Cell 'B' was ~ 78 % that of 'A' while the capacity of cell 'C' was similar to the training-set cell 'A'. As shown in Fig. 4, 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.

Table 1. Fuzzy Logic Model Rules

1. If (in1 is in1mf1) and (in2 is in2mf1) and (in3 is in3mf1)
   then (out1 is out1mf1) (1)
2. If (in1 is in1mf2) and (in2 is in2mf2) and (in3 is in3mf2)
   then (out1 is out1mf2) (1)
3. If (in1 is in1mf3) and (in2 is in2mf3) and (in3 is in3mf3)
   then (out1 is out1mf3) (1)
4. If (in1 is in1mf4) and (in2 is in2mf4) and (in3 is in3mf4)
   then (out1 is out1mf4) (1)
5. If (in1 is in1mf5) and (in2 is in2mf5) and (in3 is in3mf5)
   then (out1 is out1mf5) (1)

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



Fuzzy Logic Model Predicted SOC vs. Actual

Fig. 4a Undocumented Hawker Lead Acid, 2.5 Ah, “D"-size, Cell-“B”
RMS Error = 3.42%

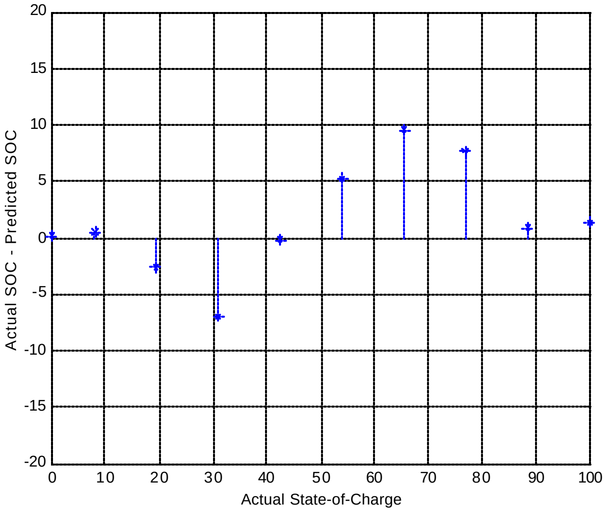


Fig. 4b Undocumented Hawker Lead Acid, 2.5 Ah, “D-size”, Cell-“C”
RMS Error = 4.86%

Fuzzy Logic Modeling of TDS data

Although three features of the TDS data were identified to vary with battery SOC, i.e. the Max-Mean Voltage, Mean-Min Voltage and the Mean voltage, an initial FL model based on just the Mean Voltage of one TDS cycle was developed.

Models were also 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

[8] 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. 5.

The model was tested using undocumented data from Cell- ‘m24’. The results are shown in Fig. 6.

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

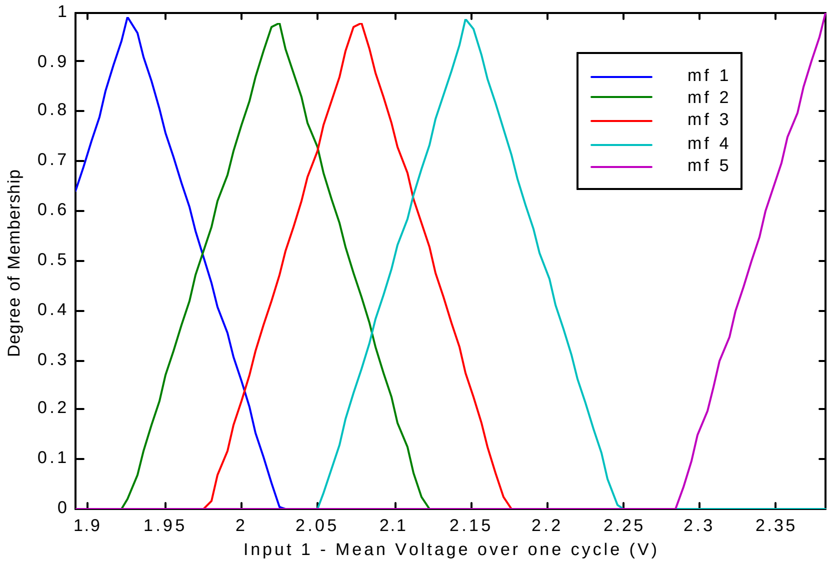


Fig. 5. SAM - FL Model Membership Functions (TDS), Input 1. Mean Voltage (V) over one TDS cycle Hawker Pb-acid, 2.5 Ah, “D”-size.

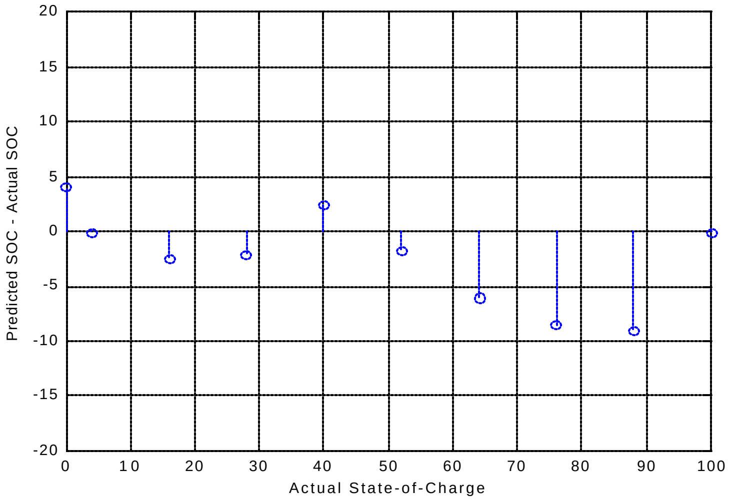


Fig. 6. SAM - FL Model Predicted SOC vs. Actual (TDS) Undocumented Hawker Pb-acid, 2.5 Ah, "D"-size, Cell - 'm24'. RMS Error = 4.73%

As can be seen through these two examples, fuzzy logic data analysis for lead acid cells can provide an accurate means of estimation battery SOC. We have also demonstrated this same approach to other battery chemistries including Li/SO_2 [11] and Li/MnO_2 [12] primary cells, and NiMH secondary batteries [13]. This approach however is generic and may be extended to any battery chemistry using virtually any interrogation technique that provides the data necessary for battery SOC/SOH estimation.

Extension to 42 Volt Systems

Clearly the combination of fuzzy logic data analysis and a battery interrogation method, such as impedance measurements, offer a powerful approach to battery SOC/SOH estimation if a data set on the battery is available. However, if the data set is new or evolving, as in the case of 42 volt systems, the fuzzy logic model must be adaptable and evolve as data is obtained. One approach is to start with a sparse data set and develop an initial model, and then have the model adaptively improve as more data is made available. This may be achieved either by using neural network-based algorithms [8] or using evolutionary computation methodologies, such as genetic algorithms [14]. In these methods, the battery monitoring system essentially "learns" about the performance of the battery system and adapts the estimation of SOC or SOH of the battery based on changing battery parameters due, for example, to aging of the battery.

Hardware for Implementation of Fuzzy Logic-Based Battery Monitoring System

A major advantage of the fuzzy logic-based battery monitoring system is the code efficiency and low cost implementation of this powerful, accurate technique. We have implemented a battery monitoring system for Li/SO_2 cells using both the 8-bit 68HC11 and the 16-bit 68HC12 Motorola microcontrollers [15,16]. We have also designed application specific integrated circuit (ASIC) chips (dedicated fuzzy hardware) for monitoring Li/SO_2 cells [17] and SLI lead acid batteries [18], both based on the coulomb counting technique. We have also designed and implemented impedance-based hardware for Li/SO_2 cells [16] and are presently designing ASICs for automotive lead acid batteries also based on the impedance interrogation method combined with fuzzy logic data analysis.

Conclusions

Fuzzy logic analysis of battery data can be used to both efficiently and accurately estimate both the SOC and SOH of batteries. The data can be measured in real time and the calculations of SOC/SOH may be performed in real time. Fuzzy logic algorithms for battery SOC/SOH estimation may be developed rapidly with relatively sparse data sets and then adaptively improve as more data is acquired. Since the fuzzy logic data analysis technique may be used with any front end battery monitoring hardware, the relative increase in system cost can be relatively low. For all of these reasons, the use of fuzzy logic data combined with battery interrogation techniques is well suited to the development of battery monitoring systems for newly developing battery technologies such as the 42 volt systems which will not have been fully characterized by the time the batteries are implemented in vehicles.

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