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Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology

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Abstract

A practical method of predicting state-of-charge (SOC) and state-of-health (SOH) of battery systems has been developed and tested for several systems. The method involves the use of fuzzy logic mathematics to analyze data obtained by impedance spectroscopy and/or coulomb counting techniques. Fuzzy logic provides a powerful means of modeling complex, non-linear systems without the need for explicit mathematical models. New detailed impedance date has been obtained on the discharge performance of primary lithium/sulfur dioxide cells. Earlier data, obtained by Rutgers co-workers on nickel/metal hydride and other systems, have been reviewed and re-interpreted using fuzzy logic methodology. Devices are being developed for several systems, which will predict the SOC and SOH of batteries without the need to know their previous discharge and/or cycling history.

Keywords: State-of-charge monitors; Impedance spectroscopy; Lithium primary batteries/sulfur dioxide; Nickel/metal hydride rechargeable batteries; Mathematical modeling; Fuzzy logic methodology

1. Introduction

The predicted available capacity of batteries, traditionally based on the chemical oxidation state (state-of-charge—SOC) of the active materials, is very important information to users of primary and secondary battery systems. It has a special significance in the cases of intermittent discharge or long shelf-life applications.

Many laboratory methods and several commercial devices have been reported and reviewed to predict this SOC status.

A more powerful performance indicator is the state-of-health (SOH) status. This relates to the ability of a cell/battery to perform a particular discharge (or charge) function at an instantaneous moment in the charge–discharge–stand-cycle regime.

The need for non-invasive and instantaneous methods for the determination of SOC and SOH became dominant with remote and/or sealed battery technology, in combination with electrical systems requiring high rate pulse performance. Three generic techniques evolved: coulomb counting, voltage (or current) pulse response, and impedance measurement.

A useful means of studying processes in electrochemical systems (including biological processes, batteries, and capacitors) is to make impedance measurements over a wide range of frequencies, usually referred to as electrochemical impedance spectroscopy (EIS). Recently, impedance data on many practical battery designs have been reported. The determinations of SOC and SOH of secondary lead-acid and nickel–cadmium batteries were reviewed by Huet [1] in 1998. His detailed article presents the underlying chemical and electrochemical theory and includes data on mid-size commercial batteries. Also noteworthy is the data and modeling of lead-acid [2,3], nickel–cadmium, nickel–metal hydride [4] secondary batteries, and some primary lithium systems [5,6], using EIS, carried out by several thesis students and staff scientists at Rutgers University over a period of more than 10 years. These projects, and other early work, relied on complex, non-linear, least squares algorithms for the extraction of equivalent circuit parameters.

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Extensive data on a lithium–iodine implanted medical battery design was presented by Schmidt and Skarstad [7,8] at the 1997 International Power Sources Symposium. EIS was utilized as a technique for monitoring aging effects in nickel/hydrogen and nickel/metal hydride batteries on aerospace qualification cycling tests by Smith et al. [9].

In our more recent work, the Fuzzy Logic Methodology developed by Singh et al. [10–13] has been applied to the interpretation of new and old data, and prototype hardware meters have been fabricated.

An impedance technique and instrument based on conventional data analysis has been developed by Atwater and Dratier at Ft. Monmouth [14]. Other early studies at Rutgers University [15–17] involved characterizing the analysis of response to current (or voltage) pulses in nickel/iron and lead-acid batteries in Rutgers data and from the technology reported by Palanisamy et al. [18]. Some of these early studies related to the capability of electric generating plants to shut down under battery power. In many applications, the batteries could not be removed for testing, and a full-time on-line instantaneous reading of SOH was the desired goal.

The fuzzy logic method is amenable to determining battery condition regardless of which of the three classical techniques of measuring SOC or SOH is employed. It also simplifies the fabrication of commercial devices, since the hardware requirements are minimized.

2. Background to fuzzy logic

Data may be categorized by 'crisp' or 'fuzzy' sets. Crisp sets categorize data with certainty, e.g., a set of temperatures between 30°C and 40°C. With fuzzy sets, a set in which data can be categorized, is uncertain, e.g., the temperature is 'warm'. This linguistic descriptor 'warm' is a subset of a set of all temperatures and is defined by its membership function. The degree to which an element of the set 'temperature' belongs to the fuzzy subset 'warm' is indicated by a quantity referred to as its 'degree of membership' or fit (fuzzy unit) value.

Fig. 1 shows an example of three subsets, defined by their membership functions, 'cold', 'warm', and 'hot', of the 'Universe of Discourse' set 'temperature'. The process

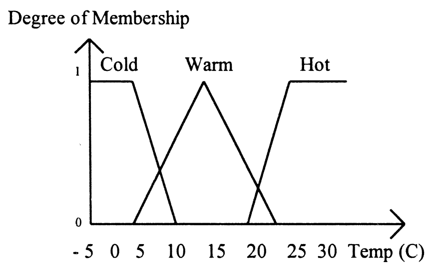

Fig. 1. Membership function for temperature.

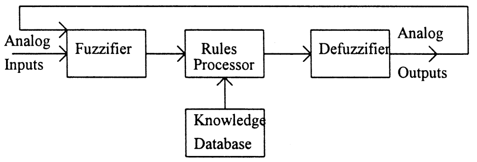

Fig. 2. A complete fuzzy inference system.

of determining the fit values of the real-valued data is referred to as 'fuzzification' of the data.

A fuzzy system is illustrated in Fig. 2 in which both the inputs and outputs are crisp sets (real-valued). The fuzzy system has four conceptual components [19]: 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, and a defuzzification block which transforms the fuzzy output sets to a crisp (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 output is low'.

The membership functions and rule set may be described by an expert or may be generated by neural networks. Unsupervised neural networks can find the initial rules and membership functions using numerical training data that describe the input–output relationship. Supervised neural networks can fine-tune the rules and membership functions generated by the unsupervised neural networks. The additive fuzzy system has been proven to be a so-called 'universal approximator' that can be used for modeling and control of complex, non-linear systems [20].

An inference system commonly used to develop fuzzy models is the Mamdani fuzzy inference system. The Mamdani approach was developed in the 1970s and was the first inference method applied to control systems. The Mamdani inference procedure is based on max–min composition, the defuzzification process is inherently computationally intensive. The effect of the max combiner on the output membership functions is to generate an 'envelope' of the fired output membership functions. In order to defuzzify this output set, the centroid of the envelope is found by integrating over the two-dimensional shape.

Another inference system commonly used is the Standard Additive Model (SAM). The SAM inference approach is based on correlation–product inference. This overcomes the loss of information associated with the correlation–min inference in the Mamdani inference method. The additive-combiner also in the SAM makes defuzzification simpler than the max-combiner of Mamdani inference. The additive-combiner also accounts for the information in the overlap of the fired output sets that the max-combiner ignores.

A more specific type of SAM is the Sugeno inference. In the Sugeno approach, the output set consists of piecewise linear function of the inputs rather than a fuzzy set.

This makes the computation of the centroid, to defuzzify the output, much easier than in the Mamdani approach—the calculation simply involves taking the weighted average of a few piece-wise linear functions. In the simplest Sugeno model, in zero-order, the output is a singleton rather than a fuzzy set. For example, a typical fuzzy rule in a zero-order Sugeno model is;

if x is A and y is B, then $z = k$

where A and B are fuzzy sets and k is a crisply defined constant [21]. The more general first-order Sugeno model has rules of the form;

if x is A and y is B, then $z = p^* x + q^* y + r$

where A and B are fuzzy sets and p, q and r are all constants.

There are two approaches to optimizing a fuzzy logic model—supervised and unsupervised learning. By tuning the input and output membership functions, the fuzzy system model may be optimized in a squared error sense. Expert feedback or a neural network algorithm, such as the back propagation algorithm, may be used to optimize the fuzzy logic model in supervised learning. In unsupervised learning, clustering algorithms may be used to find clusters in the input–output space in which initial membership functions and rules can be extracted. The system can then be fine-tuned using a neural network.

In this paper, we present our development of fuzzy models using both the Mamdani and the first-order Sugeno approach to model batteries using impedance data. Supervised and unsupervised learning techniques will be used to fine-tune the parameters of the fuzzy system in the case of the first-order Sugeno model. The fuzzy systems will be designed and simulated using the commercially available, high-level programming environment MATLAB and the Fuzzy Logic Toolbox for MATLAB.

3. Modelling of battery systems

3.1. Lithium / sulfur dioxide cells (Li / SO_2)

Preliminary EIS has been performed on primary 1.2 A h Li/SO_2 cells (PCI) using a Solartron 1250 frequency response analyzer and a PAR 273 Potentiostat/galvanostat over the frequency range of 0.65 Hz–65 kHz. The commercial software programs Zplot and Coreware (Scribner Associates) were used to collect the data. In order to demonstrate the robustness of the combined EIS and fuzzy logic technique, cells were chosen from two different

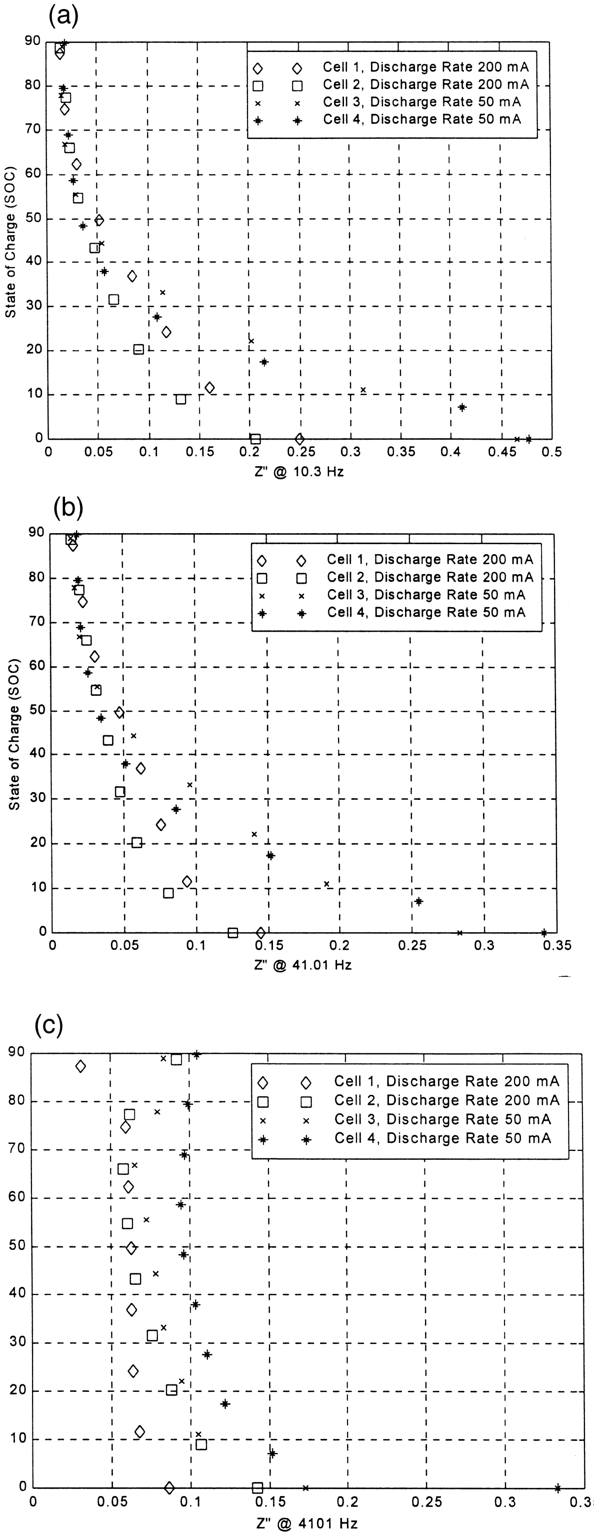

Fig. 3. (a) Imaginary component of the impedance (Z'') at 10.3 Hz against SOC; (b) Imaginary component of the impedance (Z'') at 41.01 Hz against SOC; (c) Imaginary component of the impedance (Z'') at 4101 Hz against SOC.

Table 1
Results from the Li/SO_2 experiment

Cell	Lot	Discharge rate (mA)	Total charge removed (Ah)
01	01/91	200	0.793
02	12/90	200	0.8796
03	01/91	50	0.900
04	12/90	50	0.9683

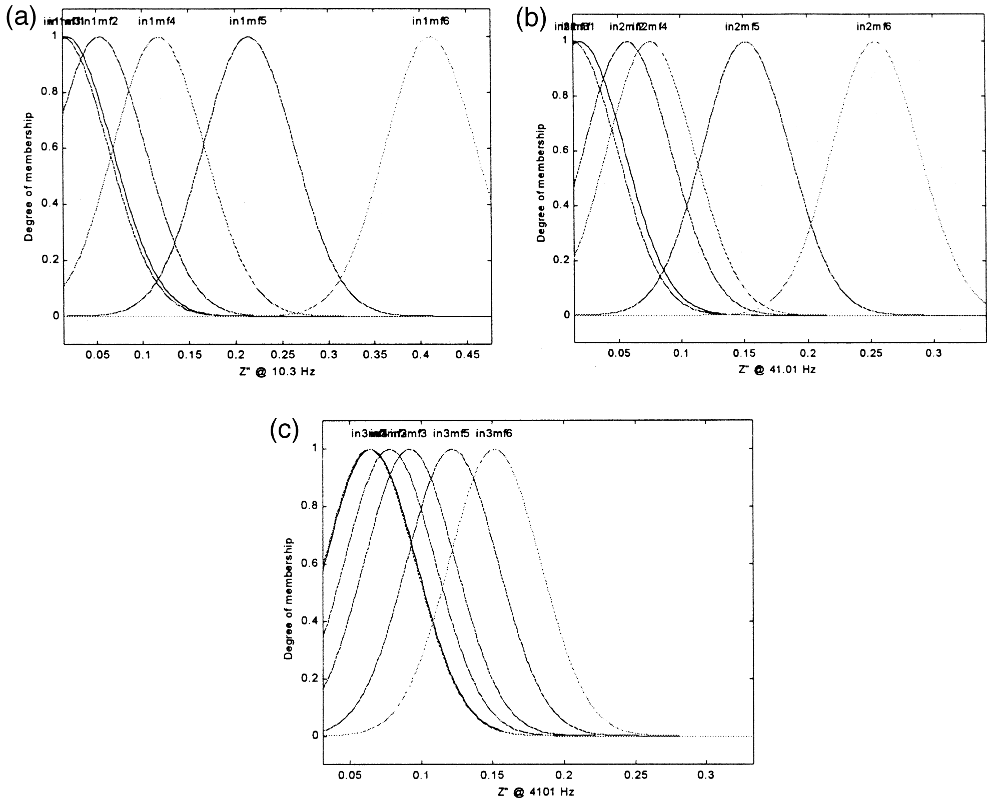

Fig. 4. (a) Input 1 membership functions for Z'' at 10.3 Hz; (b) Input 2 membership functions for Z'' at 41.01 Hz; (c) Input 3 membership functions for Z'' at 4101 Hz.

production lots. A total of four cells were measured, two at 200 mA and two at 50 mA (see Table 1). The last column in Table 1 indicates the total charge removed from the cells.

EIS was performed on each cell at successive discharge intervals of 0.1 A h until a 2 V cut-off was reached. A high current pulse of 200 mA for 30 s before each impedance measurement was used to remove the passive film that has grown on the anode. It is noteworthy that both cells from the 1/91 lot showed a capacity of ~ 0.1 A h less than the 12/90 lot cells at both discharge rates. The SOC of each cell was calculated based on the percentage of the actual total charge removed from the cell and not on the basis of the cell's nominal capacity.

To make a low-cost, practical SOC meter, unambiguous correlation between the cell's impedance at one or two frequencies (as few frequencies as possible) and the cell's SOC must be demonstrated. The imaginary component of the cell impedance at 10.3 Hz, 40.01 Hz, and 4001 Hz vs. cell SOC is displayed in Fig. 3a–c, respectively. At the two lower frequencies in Fig. 3a–b all the cell's imaginary component of the impedance appears to vary with cell SOC almost independently of the discharge rate or lot between 40% and 90% SOC. However, at the lower SOCs at the lower frequencies, and at the 4 kHz frequency over the entire SOC range, the data is seen to exhibit more spread and does not vary monotonically. This type of data does not yield to simple mathematical analysis but is well-suited to fuzzy logic modeling.

A 3-input, 1-output, fuzzy logic system based on Sugeno reasoning was developed to model the relationship between the imaginary component of the impedance at 10.3 Hz, 41.01 Hz, and 4101 Hz and the SOC of the cell. The subtractive clustering algorithm was used to develop the

Table 2
Rules for Sugeno-based fuzzy logic system for primary Li/SO_2 cells

(1) If (Z''@10.3 Hz is in1mf1) and (Z''@41.01 Hz is in2mf1) and (Z''@4101 Hz is in3mf1) then (SOC is out1mf1)
(2) If (Z''@10.3 Hz is in1mf2) and (Z''@41.01 Hz is in2mf2) and (Z''@4101 Hz is in3mf2) then (SOC is out1mf2)
(3) If (Z''@10.3 Hz is in1mf3) and (Z''@41.01 Hz is in2mf3) and (Z''@4101 Hz is in3mf3) then (SOC is out1mf3)
(4) If (Z''@10.3 Hz is in1mf4) and (Z''@41.01 Hz is in2mf4) and (Z''@4101 Hz is in3mf4) then (SOC is out1mf4)
(5) If (Z''@10.3 Hz is in1mf5) and (Z''@41.01 Hz is in2mf5) and (Z''@4101 Hz is in3mf5) then (SOC is out1mf5)
(6) If (Z''@10.3 Hz is in1mf6) and (Z''@41.01 Hz is in2mf6) and (Z''@4101 Hz is in3mf6) then (SOC is out1mf6)

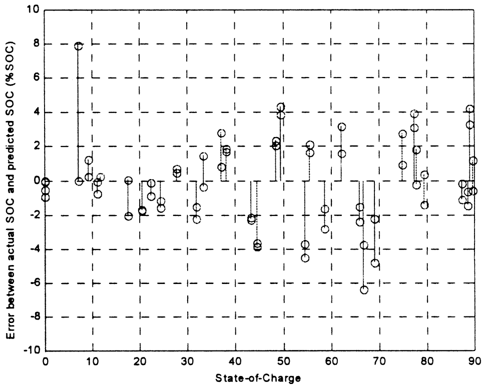

Fig. 5. Error between predicted SOC and measured SOC against measured SOC.

input membership functions displayed in Fig. 4a–c. The output membership parameters were optimized using a least squares fit. The fuzzy rules for the model are described in Table 2.

Without prior knowledge of the discharge history of the cell or the rated capacity of a lot, by measuring the imaginary component of the impedance at three specific frequencies, the fuzzy logic model that we developed predicts the SOC of a primary Li/SO_2 cell as displayed in Fig. 5. Unlike an average SOC measure, Fig. 6 shows that the maximum error between the measured SOC and the model predicted SOC throughout the entire range of measured SOC is roughly $\pm 5\%$. Therefore, the accuracy of the model is maintained throughout the entire discharge cycle of the cell. Although this model has been developed for a very limited data set, more extensive measurements are being taken to determine the model's robustness over a larger data set.

3.2. Nickel / metal hydride cells

Impedance data on nickel/metal hydride cells were obtained from the thesis of Weckesser [4,22]. The

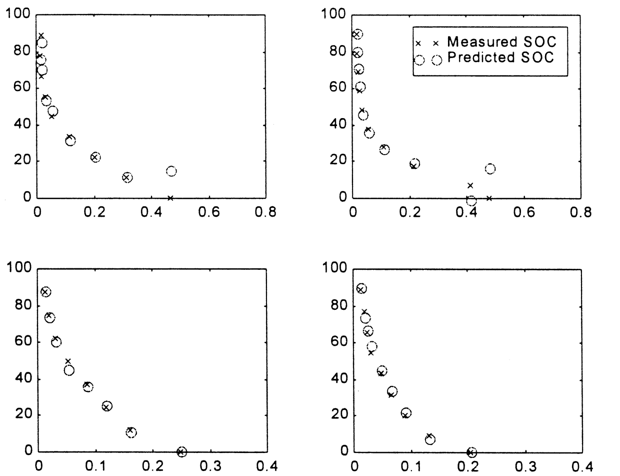

Fig. 6. Measured (xx) and model-predicted (oo) SOC against Z'' at 10.3 Hz for cell 1 (bottom left), cell 2 (bottom right) cell 3 (top left), and cell 4 (top right).

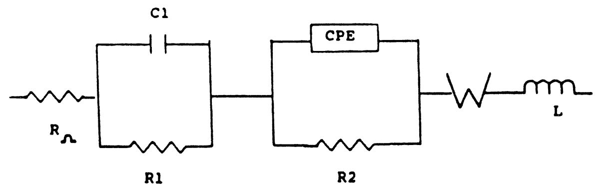

Fig. 7. Equivalent circuit used to model impedance data of nickel/metal hydride cells.

impedance data was taken at three SOCs (0%, 25%, and 100%), over a wide frequency range (0.01 Hz to 1 kHz), every 50–100 cycles over the cycle life of the cell. These data were modeled with the equivalent circuit shown in Fig. 7 below.

The values of the circuit elements were presented at each of the cycles and at each of the states of charge of the cells. The real component of the impedance Z' and the imaginary component of the impedance Z'' can be shown to be represented by the following equations in the frequency range 0.4 Hz to 1000 Hz:

$$Z' = R_{\text{ohm}} + \frac{R_1}{1+\omega^2 R_1^2 C_1^2} + \frac{R_2\left[1 + R_2 C_2\,\omega^u \cos\left(\frac{\pi u}{2}\right)\right]}{\left[1 + R_2 C_2\,\omega^u \cos\left(\frac{\pi u}{2}\right)\right]^2 + \sin^2\left(\frac{\pi u}{2}\right)} \quad (1)$$

$$Z'' = -\frac{\omega R_1^2 C_1}{1+\omega^2 R_1^2 C_1^2} + \omega L - \frac{R_2 \sin\left(\frac{\pi u}{2}\right)}{\left[1 + R_2 C_2\,\omega^u \cos\left(\frac{\pi u}{2}\right)\right]^2 + \sin^2\left(\frac{\pi u}{2}\right)} \quad (2)$$

In the above equations, u represents the exponent in the ZARC-Cole impedance $(j\omega)^u$ and the angular frequency ω is $2\pi f$, where f is the applied signal frequency. The capacitance, C_2, is a series capacitance included in the constant phase element (CPE) block in the equivalent circuit of Fig. 7. At frequencies below 0.4 Hz, the

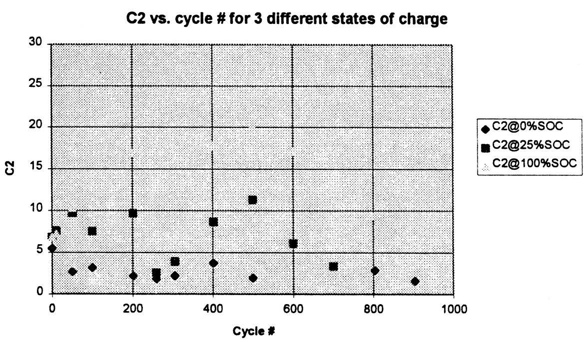

Fig. 8. C_2 capacitance as a function of SOC and cycle number.

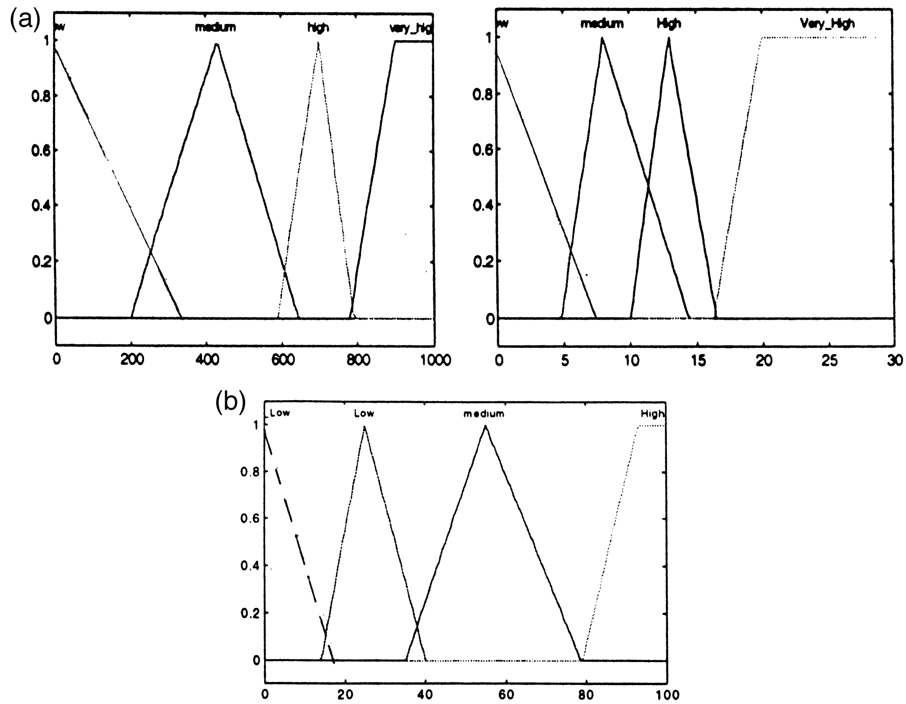

Fig. 9. (a) Input membership functions for the fuzzy logic model for nickel/metal hydride cells; (b) Output membership function for the fuzzy logic model for nickel/metal hydride cells.

impedance is dominated by the Warburg impedance (the impedance associated with diffusing species) and insufficient data was taken at the lower frequencies to model this contribution to the impedance. As a result, only the data for frequencies ≥ 0.4 Hz was used for our fuzzy logic modeling of the data.

The first stage in the modeling of the nickel/metal hydride impedance data was to reproduce Weckesser's impedance curves [22] using the circuit element values provided in his thesis. This was achieved by solving Eqs. (1) and (2) as functions of frequency, cycle number, and SOC. Using these equations, we were able to reproduce his Nyquist and Bode plots. The next step was to correlate the impedance data with the SOC and cycle number of the nickel/metal hydride cells. Our starting point in this regard was to look first at Weckesser's correlation between the C_2 capacitance and the SOC of the nickel/metal hydride cell. We calculated the variation of the C_2 capacitance as a function of frequency and as a function of cycle number at all three SOCs for which data was available (Fig. 8).

The fuzzy logic model of this capacitance data comprised a 2-input, 1-output model. The 2 inputs were the cycle number and the C_2 capacitance and the model output

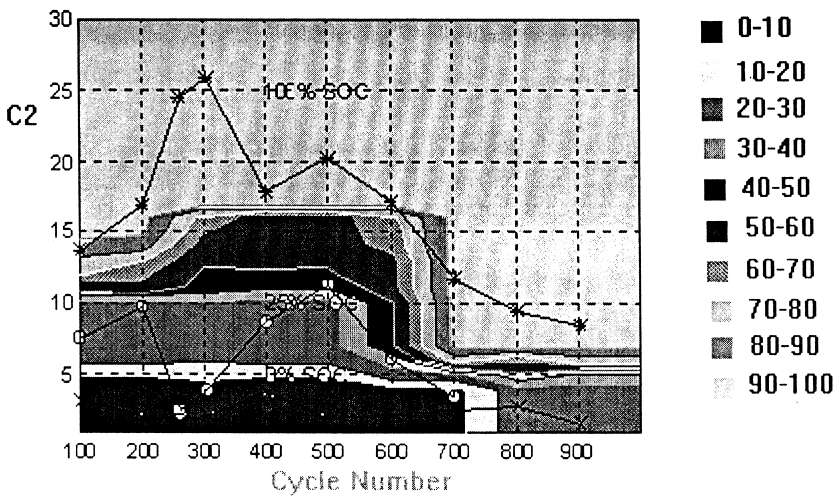

Fig. 10. Contour bands of equal SOC as functions of cycle number determined from the fuzzy logic model.

was the SOC of the cell. As can be seen from Fig. 2, the capacitance follows a monotonic variation with SOC and cycle number between 100 cycles and 600 cycles. Below 100 cycles, the C_2 capacitance does not vary smoothly as a function of cell SOC, and so our model is not applicable for this part of the cell's cycle life. Above 600 cycles, the cell is essentially at the end of its useful cycle life and so this need not be modeled. Additionally, the variation of the C_2 capacitance is seen to be quite non-linear as a function of SOC at each cycle number, making it impossible to use look-up tables and linear interpolation schemes to model this behavior. Our goal for the fuzzy logic model was to be able to determine the SOC to within 10% accuracy in the full range of useful data. The input membership functions for the model are shown in Fig. 9(a) and the output membership function is shown in Fig. 9(b). As can be seen from Fig. 9, there are four membership functions for the cycle number, four membership functions for the C_2 capacitance, and four membership functions for the SOC. Currently, 16 rules are being used in this model but this can be reduced to about 12 with further optimization of the model. Fig. 10 shows the C_2 capacitance of Fig. 8 overlaid with contours of equal SOC determined from the fuzzy logic model. As can be seen from Fig. 10, the SOC, estimated by the fuzzy logic model, is within 10% of the SOC for the 0%, 25%, and 100% cases. In between these values, the model interpolates intelligently, as a human expert would interpolate. Despite the wide fluctuation in C_2 capacitance and its non-linear relationship to SOC, the model does an excellent job of predicting the cell SOC. This is a very exciting advance in SOC estimation of cells and is completely independent of battery chemistry. There is no other equally simple approach that can emulate this level of estimation accuracy for this complex, non-linear system.

To make a practical device to estimate the SOC of a nickel/metal hydride cell, the C_2 capacitance must be extracted easily from the impedance data. Weckesser's method involved sweeping the frequency over a large range and then using complex non-linear analysis software to extract the circuit element parameters for the model. This is a cumbersome way of extracting the C_2 parameter from the impedance data and is quite expensive to implement. If this were the only way to extract the C_2 parameter, the application of this technique to cell SOC estimation would be limited to only very valuable batteries, e.g., large zinc/silver oxide cells. However, we extracted an effective C_2 parameter from the impedance data simply by measuring the impedance at two frequencies (at 0.4 Hz and at 1000 Hz). By taking the inverse of the difference of the impedance at these two frequencies, a factor closely correlating to the C_2 capacitance is obtained. A better correlation is given by taking $1/(Z$ at 0.4 Hz–$1.12Z$ at 1000 Hz) as a function of cycle number and SOC (Fig. 11). This type of function can easily be implemented in a microcontroller and would, therefore, allow a relatively low-cost, simple meter to be fabricated. Additionally, Weckesser found that the ohmic resistance of a nickel/metal hydride cell varies linearly with the cycle number.

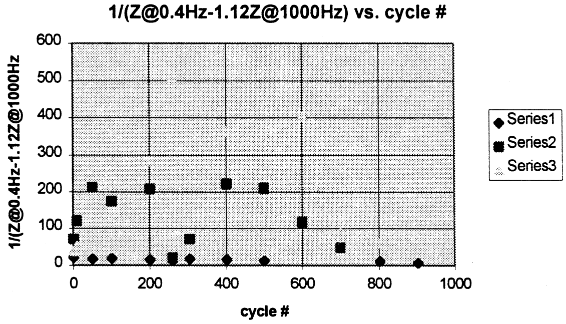

Fig. 11. Plot of $1/(Z$ at 0.4 Hz–$1.12Z$ at 1000 Hz) against cycle number for 0%, 25% and 100% SOC.

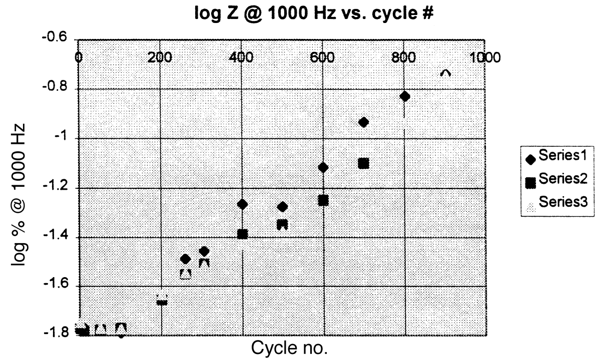

Fig. 12. Log(impedance at 1000 Hz) against cycle number for nickel/metal hydride cells at 0%, 25% and 100% SOC.

We can see this by looking at the high frequency impedance since in this frequency range, the ohmic resistance dominates the impedance of the cell. Fig. 12 shows the log of impedance at 1000 Hz as a function of cycle number and SOC. Clearly, above 100 cycles the impedance for a nickel/metal hydride cell at 1000 Hz can be used to determine the cycle number, almost independent of the SOC of the cell. By taking both the Z at 1000 Hz to give the cycle number and the $1/(Z$ at 0.4 Hz–$1.12Z$ at 1000 Hz) to give the cell SOC, a reliable and accurate SOC meter for nickel/metal hydride cells becomes viable.

4. Hardware implementation

The coulomb counting procedure using a fuzzy logic approach previously described [12] has been successfully implemented in prototype hardware. A LM35CZ temperature sensor and a 0.1 Ω resistor for current sensing were interfaced via signal conditioning circuitry to the analog-to-digital (A/D) converter lines of a Motorola 68HC11 microcontroller. The software developed to determine and display the battery SOC used four modules.

The first module samples the A/D lines, acquires the sensed current and temperature and stores them in RAM memory locations. The second module is the fuzzy logic model which determines the battery discharge efficiency as a function of current and temperature. This model was developed using TilShell software and assembled into the S-record HEX format required by the Motorola microcontroller using the AS11 assembler. The third module is a display driver that interfaces the computer to a liquid crystal display of battery SOC. The fourth module is a run time module that links the other three together and calculates the present battery SOC. The hardware has been tested with 1/3 C size lithium/sulfur dioxide cells (BA 5567) and the predicted capacities have been found to agree, within 5%, of the actual capacity.

5. Conclusions and future plans

SOC and SOH prediction has been demonstrated for two battery systems, lithium/sulfur dioxide and nickel/metal hydride, based on fuzzy logic modelling. A prototype device has been designed and tested and implementation into commercial hardware is planned.

We plan to obtain experimental data and review literature—available data on several other battery systems and designs. These include applications for EV, medical, and communication devices. The systems/designs to be studied include lead-acid, nickel–cadmium, nickel–metal hydride, lithium-ion, and lithium–MnO_2.

References

[1] F. Huet, J. Power Sources 70 (1998) 59–69.
[2] V.V. Viswanathan, A.J. Salkind, J.J. Kelley, J.B. Ockerman, J. Appl. Electrochem. 25 (1995) 716–728.
[3] V.V. Viswanathan, A.J. Salkind, J.J. Kelley, J.B. Ockerman, J. Appl. Electrochem. 25 (1995) 729–739.
[4] J.B. Weckesser, A.J. Salkind, 184th Electrochem. Soc. Meeting, Abstract #42, Oct. 1993.
[5] T. Atwater, A.J. Salkind, J. Electrochem. Soc. 145 (1998) L31–33.
[6] A.J. Salkind, J.J. Ockerman, T. Atwater, Impedance Studies on Defibrillator Batteries, UMDNJ-RWJMS Bioengineering Div./Surgery Dept. Internal Report, 1991.
[7] C.L. Schmidt, P.M. Skarstad, in: A. Attewell, T. Keily (Eds.), Power Sources 16, 20th Int. Power Sources Symposium, Elsevier, 1997.
[8] C.L. Schmidt, P.M. Skarstad, J. Power Sources 65 (1997) 121–128.
[9] R. Smith, A.V. Bray, D.K. Coates, Proc. 35th Int. Power Sources Symp., Cherry-Hill NJ, June 1992.
[10] P. Singh, C. Fennie, Jr., A Method for Determining Battery State-of-Charge Using an Intelligent System, U.S. Patent, applied for March 12, 1997.
[11] P. Singh, C.J. Fennie, A.J. Salkind, D.E. Reisner, A Fuzzy Logic Methodology to Determine State-of-Charge in Primary and Secondary Batteries, Proc. 33rd IECEC, Colorado Springs, 1998.
[12] P. Singh, C.J. Fennie, D.F. Reisner, A.J. Salkind, Proc. 38th Power Sources Conf., Cherry Hill, NJ, June 8–11, 1998.
[13] P. Singh, C.J. Fennie, D.E. Reisner, A.J. Salkind, Proc. EVS-15, Brussels, Belgium, Oct. 1998.
[14] T. Atwater, R.M. Dratier, U.S. Patent. 5,372,898, Dec. 13, 1994.
[15] A.J. Salkind, J.J. Kelley, J.B. Ockerman, B. Radimer, E. Hyman, Charging and Monitoring of Electric Vehicle and Energy Storage Batteries, Proc. ILZRO Lead-Acid Battery Seminar, Orlando, FL, May 3–5, 1989.
[16] J.J. Kelley, J.B. Ockerman, A.J. Salkind, Charging Efficiency Studies of Nickel–Iron and Other EV batteries, 178th Electrochem. Soc. Meeting Abstracts #107, Oct. 1990.
[17] A.J. Salkind, J.J. Kelley, J.B. Ockerman, Comparative study of pulse response of EV battery systems, in: T. Keily, B. Baxter (Eds.), Power Sources 13, Int. Power Sources Symp. Committee, Crowborough, UK, 1991, pp. 35–42.
[18] T. Palanisamy, S. Mendelson, D. Cipris, R. Chance, U.S. Patent 4,876,349.
[19] J.-S.R. Jang, C.-T. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing, Prentice-Hall, Upper Saddle River, NJ, 1997.
[20] B. Kosko, Fuzzy Engineering, Prentice-Hall, Upper Saddle River, NJ, 1997.
[21] Commercial Literature, The MathWorks, Natick, MA.
[22] J. Weckesser, An Evaluation of the Electrochemical Properties of Metal Hydride Alloys for Rechargeable Battery Applications, PhD Thesis, Rutgers University, 1993.