Available online at www.sciencedirect.com
ScienceDirect
Journal of Power Sources 162 (2006) 829–836
JOURNAL OF POWER SOURCES
www.elsevier.com/locate/jpowsour

# Design and implementation of a fuzzy logic-based state-of-charge meter for Li-ion batteries used in portable defibrillators

Pritpal Singh[a,*], Ramana Vinjamuri[a], Xiqun Wang[b], David Reisner[b]

[a] *ECE Department, Villanova University, 800 Lancaster Avenue, Villanova, PA 19085, USA*
[b] *US Nanocorp® Inc., 74 Batterson Park Rd., Farmington, CT 06032, USA*

Received 14 February 2005; accepted 7 April 2005

---

## Abstract

A fuzzy logic-based state-of-charge meter is being developed for Li-ion batteries for potential use in portable defibrillators. ac impedance and voltage recovery measurements have been made which are used as the input parameters for the fuzzy logic model. The load profile for the Li-ion battery packs comprises a continuous 1.4 A constant current discharge periodically interrupted by 10 A pulses. As the battery is cycled the available capacity diminishes and so the number of 10 A pulses that may be delivered decreases. Measurements are being made on a total of three battery packs at three different temperatures (0, 20 and 40 °C) and as expected the number of pulses deliverable by the battery pack diminishes as temperature is decreased. For example, at room temperature the battery pack was initially able to deliver 42 pulses early in the cycle life whereas at 0 °C the battery-pack is only able to initially deliver 12 pulses.

The voltage recovery profile upon removal of the 10 A load has been used both in the time domain and frequency domain to develop fuzzy logic models to estimate the number of remaining pulses that the battery-pack can deliver. Accurate models are being developed to estimate the number of pulses that the battery pack can deliver at various stages of its cycle life and at the different temperatures. With sufficient data collected for the battery packs at room temperature accurate fuzzy logic models have been developed for estimation of state-of-charge and implemented in the Motorola MC 68HC12 microcontroller.

*Keywords:* Voltage recovery profiles; Fuzzy logic modeling; State-of-charge; Lithium ion battery; Battery monitoring

---

## 1. Introduction

The survival rate for patients who suffer sudden cardiac arrests increases dramatically if the patients are treated within a few minutes of the cardiac event. In recognition of this fact, automated external defibrillators (AEDs) are becoming widely deployed in airports, offices, and among emergency responders, including firemen and policemen. The most common failure of AEDs is associated with failure of the battery. Indeed, recently all AEDs sold by a particular manufacturer were removed from the market due to frequent battery failure in the devices [1].

Since 1997, Villanova University and US Nanocorp® Inc. have collaborated on the development of patented fuzzy logic-based methods for determining state-of-charge (SOC) and state-of-health (SOH) of batteries [2,3].

Due to their higher energy densities compared to lead acid and nickel cadmium chemistries, lithium ion batteries are being considered for use in AEDs. The aim of the present project is to design, integrate and develop a fuzzy logic-based SOC/SOH meter for Li-ion batteries to be used in AEDs.

The goal will be to be able to take a Li ion battery pack from storage of unknown condition and using a combination of an

---

[*] Corresponding author. Tel.: +1 610 519 7378; fax: +1 610 519 4436.
*E-mail addresses:* singh@ece.villanova.edu, pritpal.singh@villanova.edu (P. Singh), ramana@ece.villanova.edu (R. Vinjamuri), xwang@usnanocorp.com (X. Wang), dreisner@usnanocorp.com (D. Reisner).

0378-7753/$ – see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2005.04.039

interrogation method and fuzzy logic data analysis, estimate both the number of times the battery has been cycled and the number of pulses it can deliver.

There are three commonly used techniques for interrogating a battery, namely coulomb counting, voltage recovery and ac impedance measurements. Each of these is described next in more detail.

### 1.1. Coulomb counting

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. Nevertheless, this is the standard technique used for battery monitoring in consumer electronic devices employing Li-ion batteries, e.g. laptop computers, camcorders, cellular phones, etc.

### 1.2. Voltage recovery

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 SOC/SOH of the battery. Since the battery is pulsed in an AED (to charge the capacitors that deliver the high voltage to the electrodes) this method is preferred since the pulsing circuitry is already built into the AED. This method is the one we used in the present project.

### 1.3. ac impedance method

The 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. Usually a single frequency is used and the resulting battery condition is estimated from the value of the impedance at the single frequency. This method has been used previously to measure SOH of Li-ion batteries [4] and we have reported its use for determining the SOC and SOH of Li-ion batteries for AED applications [5]. However, although this method can work well, the additional circuitry required to measure the ac impedance of the battery adds cost to the AED unit.

In this paper, we describe how voltage recovery profiles in response to a load stimulus were measured on Li-ion batteries at different SOCs. We then describe fuzzy logic models, which accurately estimate the SOC from the voltage recovery profile data. Finally, we describe a prototype hardware implementation of a SOC meter for this application using a Motorola MC68HC12 microcontroller.

## 2. Experimental

The Li-ion battery packs characterized in this project comprised twelve Sanyo 18650 cells in a 4 series × 3 parallel arrangement with a 300 mΩ in-line fuse to simulate the protection circuitry for the battery pack. These battery packs are to be employed in AEDs and so a recommended discharge profile comprises two current states. The first current state is a low, steady current of 1.4 A for heart beat monitoring and EKG acquisition. The second current load state on the defibrillator battery pack is high current pulse discharges of 10 A to charge capacitors which provide the high voltage pulses to the paddle electrodes used to electrically stimulate the heart.

A test procedure was implemented to simulate this discharge profile as indicated below:

1. Constant current discharge at 1.4 A for 5 min.
2. Constant current discharge at 10 A for 5 s.
3. Repeat this process (steps 1 and 2) for a total of 1100 s, which includes three 10 A discharges.
4. ac impedance measurement over frequency range of 1 Hz to 1 kHz.
5. Repeat above four steps until end of discharge is reached (2.5 V cell$^{-1}$).

Fig. 1 shows a graphical display of the load test profile.

The current discharge was performed using an Agilent Technologies 6063B electronic load, which in turn was controlled by HPVEE software and monitored by a Solartron 1280B Electrochemical Measurement Unit (EMU). The Solartron 1280B was used to measure the open circuit voltage (OCV) of the battery pack. After the current discharge was completed an impedance measurement was taken by a combination of the Solartron 1280B EMU and a Solartron 1290 Power booster (used to increase the voltage range of the Solartron 1280B.)

Battery packs usually displayed a starting voltage of around 16.7 V and as they deliver high current pulses the

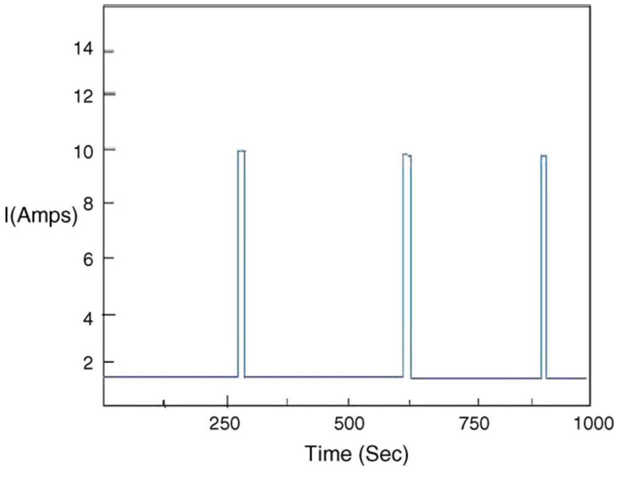


Fig. 1. Load current profile 1.4 A base with 10 A peaks.

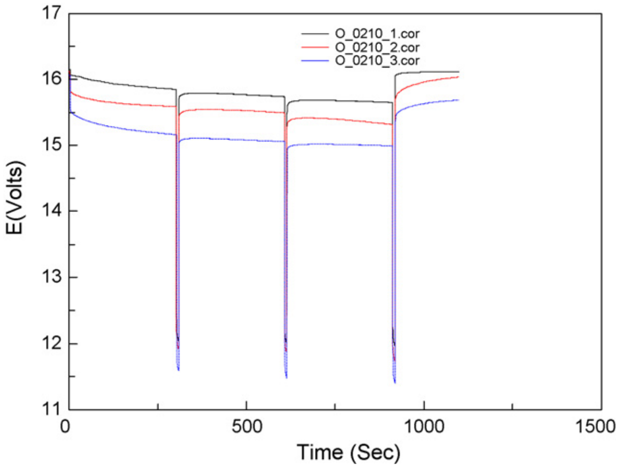


Fig. 2. Voltage recovery curves for the battery pack 0 °C for 100th cycle.

voltage of the battery pack gradually decreases. The end of discharge voltage of the battery pack was taken to be 10 V. When the battery is completely discharged it is recharged by a Centronix BMS 2000 battery management system. Typically it takes 150 min to fully charge the battery pack. A Tenney environmental oven (with digital temperature control) was used which was employed to perform the measurements at different temperatures.

### 2.1. Experimental results

Results obtained are mainly two types of measurements that are obtained from the test process. They are the voltage recovery measurements and the Impedance measurements. Each of them is shown below for a complete cycle of discharge for the battery pack operated at 0 °C, which includes nine pulses and three impedance measurements.

Fig. 2 shows the voltage recovery measurements for one complete cycle of discharge for the battery pack at 0 °C.

A total of nine pulses are shown and it is observed that the voltage of the battery pack gradually decreases and the minimum voltage obtained from the battery pack when load current is 10 A also decreases gradually with increase in the number of pulses. Fig. 3 shows three ac impedance measurements obtained from the battery pack. As we can see both in the Complex plot and the Bode plot as the pulse number increases these curves move down.

## 3. Fuzzy logic modeling

Before the Fuzzy logic modeling could be performed, the data was preprocessed to obtain the correct input parameters for the model.

### 3.1. Preprocessing

The data obtained from the voltage recovery profiles was analyzed numerically and two types of curves were obtained from the analysis: the minimum voltage curves and difference voltage curves. A minimum voltage curve is the locus of all the minimum voltage points that are obtained in a single cycle of the battery pack. Here the minimum voltage corresponds to the minimum voltage of the battery pack at 10 A load current. A difference voltage point refers to the difference between the maximum and minimum voltages of the battery pack. Here maximum voltage refers to the voltage of the battery pack when load current is 1.4 A just before the 10 A discharge peak. The locus of all these difference voltage points forms a difference voltage curve. One such minimum voltage curve and a difference voltage curve exist for one

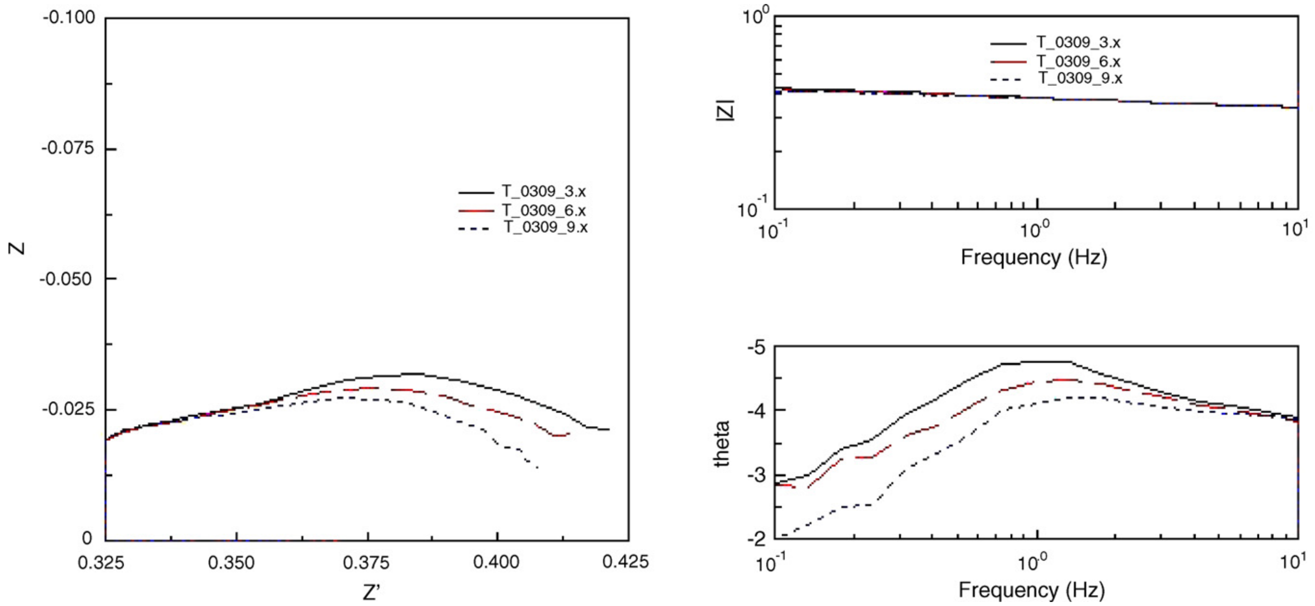


Fig. 3. ac impedance measurement—Complex plot to the left (imaginary $Z$ vs. real $Z$) and Bode plot to the right (|$Z$|, theta vs. frequency).

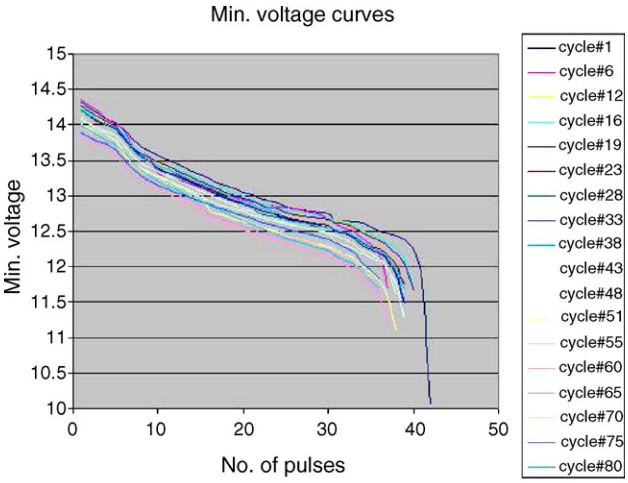


Fig. 4. Minimum voltage curves (min. voltage vs. no. of pulses).

cycle of a battery pack. A total of two sets of 80 such curves which were obtained from the analysis of 80 cycles of data over the battery pack at 20 °C (room temperature) are used in this analysis.

Fig. 4 shows a set of minimum voltage curves together with corresponding cycle numbers. It is observed that as the cycle number increases these curves monotonically move down with the cycle number.

Fig. 5 shows a set of difference voltage curves together with the corresponding cycles numbers. It is observed that as the cycle number increases these monotonically move up with the cycle number.

Interestingly, the same type of behavior in minimum voltage curves and difference voltage curves was observed at 0 °C for these battery packs. By observing the behavior of the curves shown above it is proved that minimum voltages and maximum voltages of the battery pack are useful parameters in determining the state-of-charge and state-of-health of the batteries.

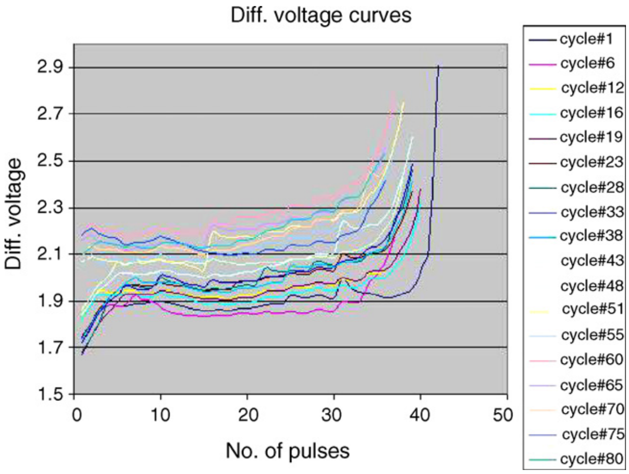


Fig. 5. Difference voltage curves (diff. voltage vs. no. of pulses).

### 3.2. Modeling

After preprocessing the data, two different sets of parameters minimum voltage/4 and maximum voltage/4 were obtained which correspond to state-of-charge and state-of health. Here the voltages are divided by 4 in order to reduce them to the input voltage range for the A/D converter on the microcontroller (0–5 V).

The Sugeno type of Inference method was adopted for developing the fuzzy logic model.

For instance—for SOC model:

IF (Min1 is Min_1) and (Max1 is Max_1) then SOC is 35
. . .
IF (Min2 is Min_*n*) and (B is Max_*n*) then SOC is 2

For SOH model:

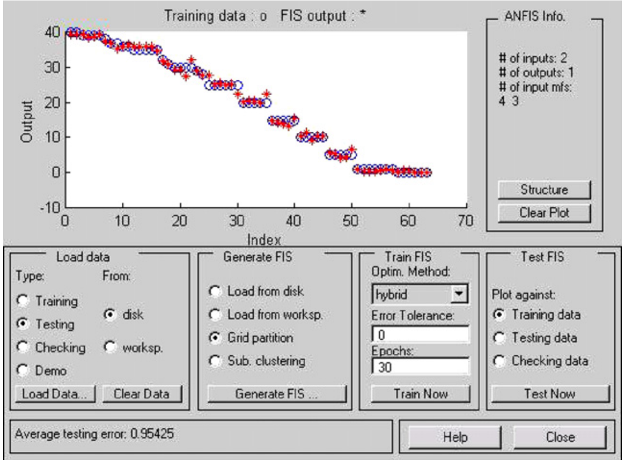
IF (Min1 is Mn_1) and (Max is Mx_1) then SOH is 80
. . .
IF (Min1 is Mn_*n*) and (Max is Mx_*n*) then SOH is 10

### 3.3. Final fuzzy logic models

Finally, two fuzzy logic models were obtained one for the state-of-charge and one for the state-of-health. Each of these models is discussed below. The fuzzy logic toolbox of Matlab® was used in developing these models.

### 3.4. Model to predict the state-of-charge

Both training and testing data were obtained from the data that was collected. The maximum and minimum voltages of even numbered cycles were used as training data and those of odd numbered cycles were used as testing data. In order to generate a fuzzy inference system (FIS), the grid partition method was used. Here four trapezoidal membership functions were assigned for the first input (maximum voltage/4) and three trapezoidal membership functions were assigned for the second input (minimum voltage/4). Figs. 6 and 7 show


Training data : o FIS output : *

ANFIS Info.
# of inputs: 2
# of outputs: 1
# of input mfs:
4 3

Load data
Type: From:
○ Training
● Testing
○ Checking
○ Demo
● disk
○ worksp.

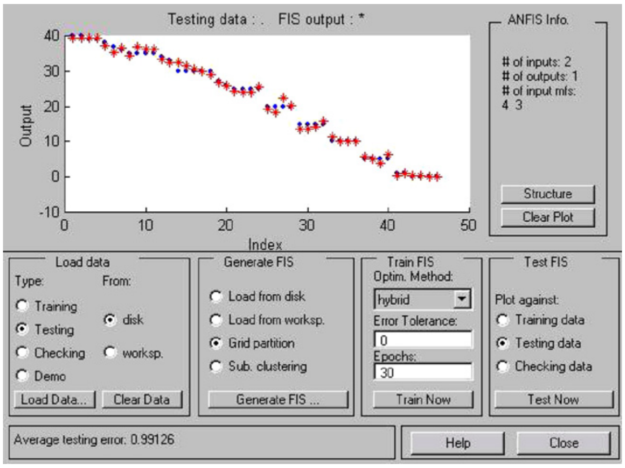
Generate FIS
○ Load from disk
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 30

Test FIS
Plot against:
● Training data
○ Testing data
○ Checking data

Average testing error: 0.95425

Fig. 6. Training error (0.95).



ANFIS Info.
# of inputs: 2
# of outputs: 1
# of input mfs:
4 3

Load data
Type: ○ Training ● Testing ○ Checking ○ Demo
From: ● disk ○ worksp.

Generate FIS
○ Load from disk
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 30

Test FIS
Plot against: ○ Training data ● Testing data ○ Checking data

Average testing error: 0.99126

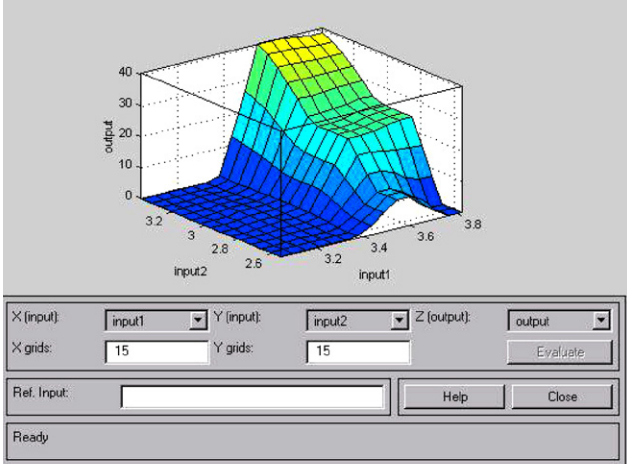
Fig. 7. Testing error (0.99).

the training error and the testing error obtained from the modeling, respectively.

A training error of 0.95 and a testing error of 0.99 are not significant over a period of 80 cycles. Hence, a good model to predict the state-of-charge has been developed. The 3D surface plot between the output and the two inputs is shown in Fig. 8. The smooth surface indicates that the model developed has good generalization ability.

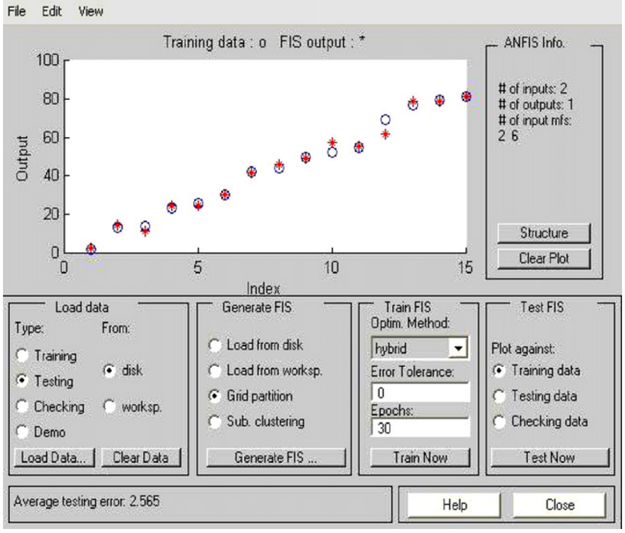
### 3.5. *Model to predict the state-of-health*

Both training and testing data were obtained from the data that was collected. The maximum and minimum voltages of even numbered cycles were used as training data and those of odd numbered cycles were used as testing data. The grid partition method was again used to generate the initial fuzzy inference system (FIS). Here two trapezoidal membership functions were assigned for the first input (maximum voltage) and six trapezoidal membership functions were assigned for the second input (minimum voltage). The SOH model was not implemented in hardware (because sufficient time for testing the model was not available). Hence the inputs used were simply the maximum and minimum voltages (not divided by 4 as in the state-of-charge model.) Figs. 9 and 10 show the training and testing errors obtained from the modelling, respectively.



X (input): input1
Y (input): input2
Z (output): output
X grids: 15
Y grids: 15
Ref. Input:
Ready

Fig. 8. 3D surface plot (SOC).



ANFIS Info.
# of inputs: 2
# of outputs: 1
# of input mfs:
2 6

Load data
Type: ○ Training ● Testing ○ Checking ○ Demo
From: ● disk ○ worksp.

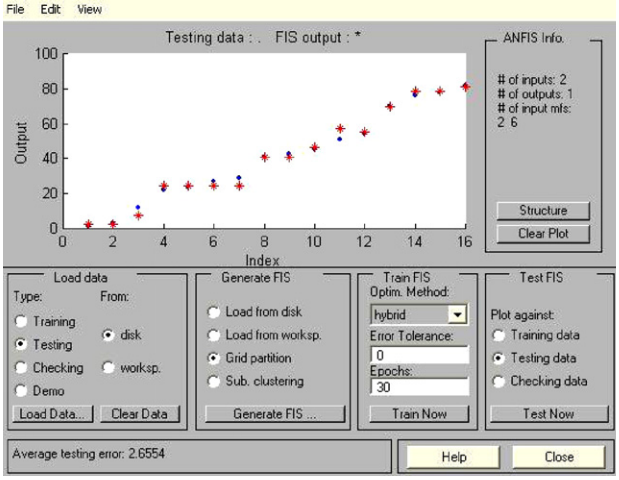
Generate FIS
○ Load from disk
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 30

Test FIS
Plot against: ● Training data ○ Testing data ○ Checking data

Average testing error: 2.565

Fig. 9. Training error (2.565).



ANFIS Info.
# of inputs: 2
# of outputs: 1
# of input mfs:
2 6

Load data
Type: ○ Training ● Testing ○ Checking ○ Demo
From: ● disk ○ worksp.

Generate FIS
○ Load from disk
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 30

Test FIS
Plot against: ○ Training data ● Testing data ○ Checking data

Average testing error: 2.6554

Fig. 10. Training error (2.655).

A training error of 2.565 and a testing error of 2.655 are not significant over a period of 80 cycles and these high power Li-ion batteries are capable of delivering even up to 450 cycles in their lifetime. Hence a good model to predict the state-of-health was developed. The 3D surface plot between the output and the two inputs is shown in Fig. 11.

## 4. Implementation of the model in microcontroller (Motorola MC68HC12)

The fuzzy logic model to estimate the SOC of the Li-ion AED battery pack, and correspondingly, the num-

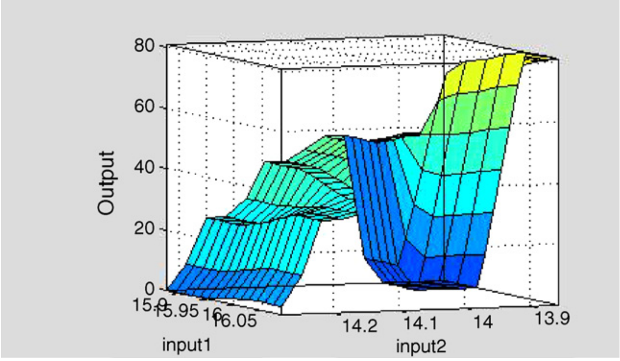


Fig. 11. 3D surface plot (SOH).

ber of pulses that it may deliver, was implemented in a Motorola MC68HC12 microcontroller. This microcontroller was selected because it includes fuzzy logic instructions in the instruction set for the processor making it straightforward to implement fuzzy logic models.

The process that we implemented in the microcontroller runs parallel to the testing circuit. The testing circuit consists of an electronic load, a PC to run the electronic load, a step-down circuit (a voltage divider network and an op-amp), a breadboard and a battery pack. For testing the battery pack we extract one pulse from it. The duration of this pulse is for 5 min and 5 s. For 5 min the discharge current is 1.4 A, and for 5 s 10 A is drawn from the battery pack by the electronic load. Throughout this process the terminals of the battery where the voltage is to be monitored are connected to the step-down circuit and the output from this circuit is fed to the microcontroller. The step down circuit is necessary because the input voltage range of the A/D converter on the microcontroller is 0–5 V. The step-down circuit gives the input voltage divided by 4 as output. This output is fed to the A/D terminals of the microcontroller. The testing circuit is shown in Fig. 12 below.

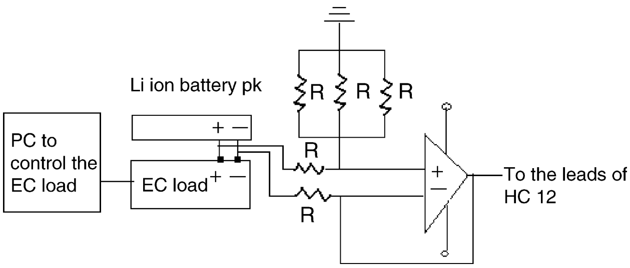


Fig. 12. Testing circuit ($R = 511\ \mathrm{k}\Omega$, Op-amp = LMC60 42 AIN).

Voltages obtained from this step-down circuit, which are fed to the microcontroller, are converted into digital signals by the on-chip A/D converter of the 68HC12 microcontroller and these signals serve as the inputs to the fuzzy logic model. Fig. 13 shows the timing diagram for the total process. A flowchart of the program written into the microcontroller to execute the acquisition of the measured input signals, processing of these signals with the fuzzy logic model, and output of the remaining number of pulses to a liquid crystal (LCD) display is shown in Fig. 14.

Both the microcontroller and electronic load are switched on at the same time. As the flow chart of Fig. 14 indicates a delay program is run for 4 min 55 s. This is the time when electronic load in the testing circuit draws 1.4 A current. There after the A/D conversion process of the microcontroller starts and it stores the values for 12 more seconds. This includes the time when electronic load draws 1.4 A for 5 s, 10 A for 5 s and 1.4 A for 2 more seconds to observe the recovery. There are 24 values stored in 24 memory locations of the microcontroller on chip memory. These are sorted and maximum and minimum voltages are picked from the collected 24 values. Now these maximum and minimum voltages serve as inputs to the fuzzy logic model. The output obtained from the model is in range 00H–FFH. This is converted to the normal pulse number range (0–40) and then it is converted to decimal. The output obtained is shown on LCD display.

The model was implemented practically as shown in Fig. 14. The complete model including electronic load, Li-ion battery pack, microcontroller, LCD display, OpAmp step-down circuit on a bread board and the power supply to the bread board are shown in Fig. 14.

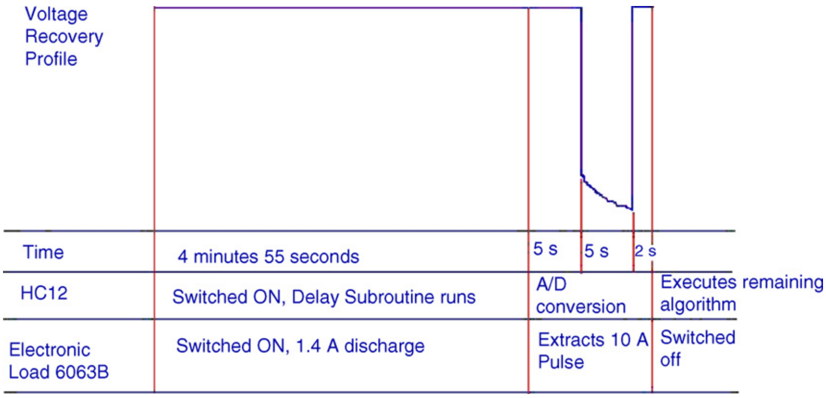


Fig. 13. Timing diagram of the testing procedure.

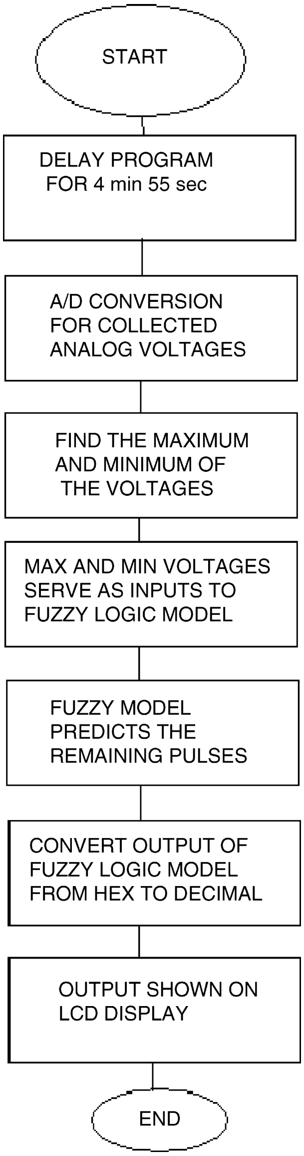


Fig. 14. Flow chart of the main program.

### 4.1. Testing of the model

The testing of the model involved one complete discharge cycle (40 pulses) of the battery pack and monitoring the output after every pulse. The battery pack at room temperature usually delivers 40 pulses. The electronic load draws one pulse for 5 min 5 s from the battery pack and then it is stopped. The voltage of the battery pack is usually in order of 14–16 V. This voltage cannot be given directly as input to the microcontroller because the supply voltage of the microcontroller is 5 V. Hence the terminals of the battery are connected to a step-down circuit, which consists of an op-amp and a voltage divider circuit (Fig. 11). This circuit is shown on a bread board in Fig. 15. The step-down converter receives its power from a 10 V supply as shown in Fig. 15. The output from the step-down circuit is monitored by the A/D pins of the microcontroller for the last 12 s of the pulse, which acquires the voltage of the battery pack during discharge (this time period covers the maximum and minimum voltages required as inputs for the fuzzy logic model). This acquired data is stored in 24 memory locations of the SRAM of the microcontroller. As shown in the flow chart (Fig. 14) the maximum and minimum values are obtained from the acquired data. These serve as inputs to the fuzzy logic model, which predicts the pulse number. But the pulse number predicted is in HEX format and is in the range from 00H to FFH. This is scaled down to give the output, which is remaining pulse number, which appears on the LCD display.

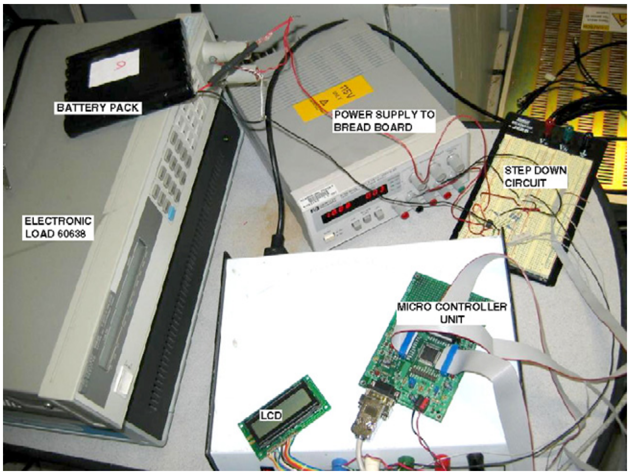


Fig. 15. Photograph of the complete SOC meter.

A stem plot predicting the error in the results of the practical implementation is shown in Fig. 16. A maximum of 3 pulses error is observed during the pulse numbers 18, 14 and 3. At all the remaining pulse numbers the error is below 3. Especially during the end of discharge the error is considered acceptable because the battery can be protected from over discharge. Additional battery packs on which the model was

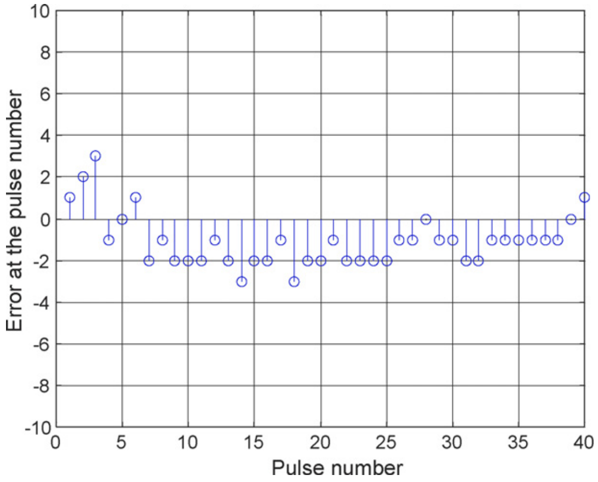


Fig. 16. Stem plot indicating the error in the pulse number.

not developed were tested and similar accuracy was obtained on two other battery packs indicating the robustness of the technique!

## 5. Conclusions

The main goal of the project was to develop a SOC/SOH meter to estimate the condition of Li-ion battery packs to be used in portable defibrillators at all temperatures. In this process ac impedance and voltage recovery measurements were obtained on the battery packs at room temperature and 0 °C. Enough data was collected for the modeling of the voltage recovery profiles which lead us to minimum voltage curves and difference voltage curves. These curves show monotonic variation of minimum voltage and maximum voltage with cycle number. The parameters obtained from the preprocessing of the data were utilized in developing fuzzy logic models for predicting both the cycle number and remaining pulse number for the battery packs at room temperature. Good fuzzy logic models were developed, with an error below one pulse to predict the number of remaining pulses and with an error of 2.5 to predict the cycle number. These are derived from the voltage recovery profiles of the battery pack at room temperature cycled for a period of 82 cycles. Finally, due to its practical importance, the model to predict the pulse number was chosen and successfully implemented in a Motorola MC68HC12 microcontroller. An average error of ±2 pulses was achieved practically both on the battery pack used to develop the model as well as in “blind testing” of battery packs not used for model development.

The SOH model still needs to be implemented and tested. Furthermore, models still need to be developed for other temperatures. We are in the process of completing the data collection at other temperatures. Once this has been done, the models will be developed and implemented in the same hardware platform and tested.

## Acknowledgements

The authors are grateful to Stephen Johnson of Medtronic Corp. for supplying the Li-ion battery packs that were measured in this study and for useful discussions. This work was supported by a Phase II STTR grant (Grant no. 2R42HL64984-02) from the National Institutes of Health.

## References

[1] Flawed Device Puts FDA Under Scrutiny, The New York Times, pg. 1, December 15, 2004.

[2] P. Singh, C. Fennie, A method for determining battery state-of-charge using intelligent systems, U.S. Patent No. 6,011,379 (January 4, 2000).

[3] P. Singh, C. Fennie, D.E. Reisner, A method for determining battery state-of-health using intelligent systems, U.S. Patent No. 6,456,988 (September 24, 2002).

[4] J.P. Fellner, G.J. Loeber, S.S. Sandhu, Testing of lithium-ion 18650 cells and characterizing/predicting cell performance, J. Power Sources 81/82 (1999) 867–871.

[5] P. Singh, R. Vinjamuri, X.Q. Wang, D.E. Reisner, Fuzzy Logic Modeling of EIS Measurements on Li-ion Batteries, in: Proceedings of the Sixth International Symposium on Electrochemical Impedance Spectroscopy, Cocoa Beach, FL, May 17–21, 2004.