FUZZY AND ANN APPROACHES FOR PREDICTION OF RETAINED CAPACITY OF BACK UP POWER SOURCE IN GEO SPACECRAFTS

S. RAMAKRISHNAN *, S. VENUGOPALAN, A. EBENEZER JEYAKUMAR*****

* Research Scholar Anna University , Chennai, India, Phone: 919841192930, E-mail: jkang69@yahoo.com
** Head, Battery Division , ISAC Bangalore, India, Phone: 918025083523, E-mail: gopal542006@gmail.com
*** Director, SREC, Coimbatore, India, ,Phone: 9198487282966, E-mail: ebeyjkumar@gmail.com

Abstract: Capacity of the batteries degrade (fade) with calendar life. Fuzzy logic and ANN models are developed to predict the retained capacity. The Developed models are compared and validated using statistical method and Bland Altman plot. Both Fuzzy and ANN models are able to predict the retained capacity more accurately within a test dataset and ANN model is recommended for extrapolation.

Key words: *Neural Network, Lithium-ion Batteries, fuzzylogic, GEO Spacecrafts*

1. Introduction

The GEO satellites are widely used for telecommunications, television & radio broadcasting, weather forecasting, disaster management, telemedicine and have a number of important defense and intelligence applications. Lithium-ion batteries are used as back up power source in GEO spacecrafts to provide energy during eclipse and peak power demands. In the GEO satellites the degradation of a lithium ion cell comprises of two parts. One due to cycling and the other due to calendar life. In GEO satellites, solar panel support the total load during solstice and most of the time, the lithium ion batteries will be on open circuit stand. Batteries will come into operation only during equinox. There are two eclipse seasons in a year lasting for 45 days each. The eclipse duration in a season varies parabolically to a maximum of 72 minutes and falls back to zero. This leads to a cycle degradation limited to 1350 cycles for the entire life span of the satellite. Hence storage degradation plays a major role in the capacity fade of batteries in GEO satellite applications. The performance and the lifespan of the Lithium-ion batteries in GEO are predominantly dependent on operating temperature and state of charge over the life [1,2].

Lithium-ion batteries are complex non linear electro chemical system [3]. Finding the Degradation in real time due calendar life for various states of charge at different temperatures is tiresome and time consuming. So there is a need for modeling to predict the degradation over life time at different temperatures and state of charge (SOC).

This paper presents model based prediction of retained capacity due to the effect of state of charge and temperature over calendar life using techniques such as fuzzy and ANN which are useful in modeling non-linear systems to a greater accuracy [4,5]. The principle constituents of modeling approach for the problems are fuzzy logic, neural network. The fuzzy model can be designed using number of techniques. In this paper it is presented with the popular Mamdani model [6].

Even though there are number of architectures and learning algorithms available to design an ANN model, a feed forward network with back propagation learning algorithm is recommended for problems where there is no explicit relationship between input and output variables [7]. In the present work two different models have been designed, one with fuzzy and the other with ANN. Comparisons between these models are made using statistical methods and Bland Altman plot to find the better model [8]. The focus is on the development of a model in addition to study the effect of state of charge on retained capacity over the life time of lithium-ion batteries.

2. Need For Models

Battery development has used “build and test” approach for meeting the requirements of the battery for any spacecraft application. However, the complete testing is expected to consume a lot of time and hence a requirement for alternatives. To achieve this objective, proven models utilizing advanced design tools that can link design features with desirable performance attributes, is recommended. Towards this end, a model-based testing approach has been implemented using fuzzy logic and ANN techniques for Lithium-ion batteries, to estimate the retained capacity for various states of charge. A battery comprises of a complex set of interacting physical and chemical processes, the purpose of which is the conversion of chemical energy into electrical energy [9]. The processes are often strongly influenced by the battery environmental conditions and use profile.

In fact, due to the number and complexity of the processes taking place, and the inability to accurately describe them, it is not possible to develop an accurate battery model. However, attempts were made to model cell behavior using different approaches [10].In this paper, two techniques one with fuzzy logic and the other with ANN have been implemented to simulate lithium battery for the prediction of retained capacity at various states of charge for GEO spacecraft applications.

3. Cell Test Set-Up

Experiments were performed using Maccor series 4000 battery/cell test system. The cell test system is designed specifically for running multi-channel high speed tests on cells. The system is modular in design with 48 channels. The system allows a batch of cells to be tested independently for various parameter settings such as state of charge, temperature etc. For example, to test the life expectancy with respect to a specified state of charge at a specific temperature the set-up allows a group of cells to be charged at any specified temperature to a predetermined voltage level. The system makes use of analogue control loops for smooth control of applied signals.

For the present problem retained capacity of lithium-ion cells have been tested for states of charge of 25%, 50% and 100% at temperature settings as tabulated in Table 1.

Temperature	State of Charge
0 ° C	25%
	50%
	100%
20 ° C	25%
	50%
	100%
40 ° C	25%
	50%
	100%

Table 1.Test data set parameters.

4. Artificial Neural Networks (ANNs)

ANN works as a substitute for autocorrelation multivariate regression, linear regression and other statistical analyses [11]. ANN allows interpretation of data, especially when the input data is noisy. Using ANN it is possible to enable patterns to emerge which are hitherto not apparent to non – experts. ANN works on the basis of three important parameters, namely, architecture, learning algorithm and the transfer function. Many typical problems can be easily solved by defining these parameters clearly. Different approaches to solution of problems are possible with variations of these parameters. Amongst various algorithms that are available for training the network, back-propagation algorithm has been identified as the most versatile and robust. BPN makes it possible for solving problems of pattern recognition and extrapolation. Our ultimate objective is to simulate complex electrochemical systems such as lithium-ion batteries used in satellite, for the evaluation of its life.

5. Fuzzy system

Fuzzy system works on the basis of fuzzy set. In general sets are defined basis on some boundaries. Any particular variable may or may not belong to the set. However, in fuzzy set, the transition between “belonging” and “not belonging” to a set is not a discrete step but gradual. The transition is defined based on membership function. The membership may be defined either in discrete form or as a continuous function. These are specified for a range of values for the variable. Some of the widely used membership functions are triangle, trapezoidal, Gaussian or bell functions. In this paper a Gaussian function as described in equation 1 is considered [12].

$$f(x,\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

Fuzzy systems are able to provide solutions to different problems based on fuzzy inference system, fuzzy rules (rule base) and fuzzy reasoning. Using these, it is possible to have non linear mapping between input and output space. There are many fuzzy modeling methods are available. In the current work Mamdani model is used.

The operations of the Mamdani rule base is over different stages. In the first stage fuzzification is done by mapping each of the crisp inputs into a fuzzy variable using membership functions followed by fuzzy antecedents which determine the output of each given rule. The next step is to combine these fuzzy outputs into a single fuzzy output. Mamdani defines that the output of the rule base should be the maximum of the outputs of each rule to determine the aggregate output of all of the fuzzy rules. This fuzzy output is converted into a crisp output by defuzzification [13,14].

6. Fuzzy Battery Model.

Fuzzy model of battery is designed using Mamdani rule base with temperature, SOC, calendar life in years as input parameters and retained capacity in percentage as the output. Inputs and output are fuzzified with Gaussian membership function. To get the crisp output, centraoid defuzzification method is employed. The configuration of fuzzy model to estimate the retained capacity is

No of inputs = 3
No of membership function for input 1 = 5
No of membership function for input 2 = 5
No of membership function for input 3 = 9
No of output member function = 52
Type of membership function = Gaussian
No of fuzzy rules = 65

Fuzzy input and output membership function for battery model are shown is figure 1, 2, 3, 4.

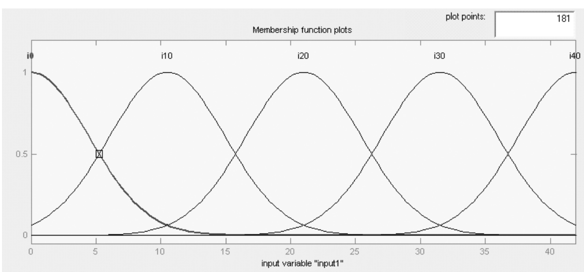

Fig.1. Membership function plot for input 1 –Temperature.

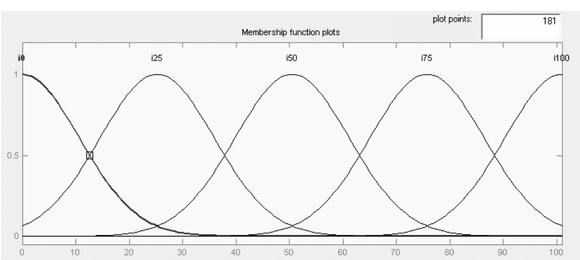

Fig.2. Membership function plot for input 2 –Charge level.

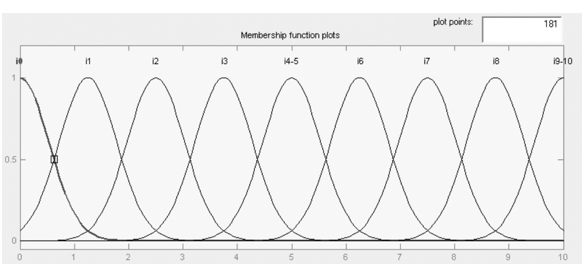

Fig.3. Membership function plot for input 3 –Test duration in years.

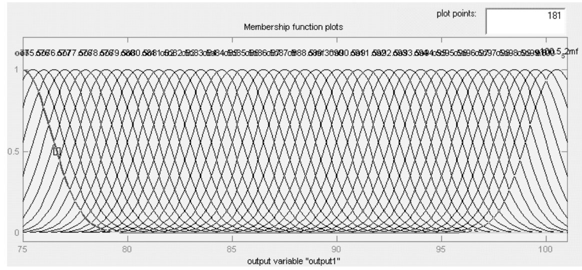

Fig.4. Membership function plot for output – Retained capacity.

7. ANN Architecture For Battery Model

A feed forward error back propagation network is adapted for the present problem to estimate retained capacity for various SOC with respect to the temperature and calendar life. The input layer consists of three neurons presented with the parameters SOC, temperature and calendar life. The output layer consists of one neurons - retained capacity. Different configurations have been tested to find the number of hidden layers and number of neurons in each layer. Out of the tested configurations the configuration with two hidden layers having five neurons each is found to be suitable for the present problem. The final configuration of the network is chosen to be three neurons in the input layer, two hidden layers with five neurons each and one neuron in the output layer as shown in figure 5.

The network has been trained with the 128 observed data sets with a learning rate of 0.4 with sigmoidal activation function. It took more than 30000 epochs to train the network to achieve error target of 0.5%.

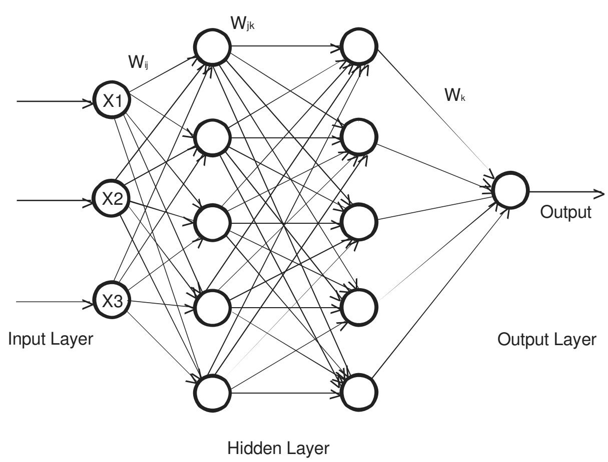

Fig.5. Back Propagation Neural Network

8. Results From fuzzy model

The observed and predicted retained capacity of lithium-ion battery for various state of charge such as 25%, 50% and 100% over seven and half years storage at different temperatures have been plots in figure 6.

It is observed from the graph that fuzzy model is able to predict to a reasonable accuracy. It is seen that at 100% state of charge and 20°C, deviation is slightly higher. The Average absolute percentage errors (AAPE), correlation coefficient, coefficient of variation between the observed and predicted values are taken as performance measures. The correlation coefficient between the observed and predicted is 0.9855 and AAPE is 0.467%. The coefficient of variation is 0.0056. These results indicate that the fuzzy model can predict accurately. As the number of rules generated influences the performance of the fuzzy model the designed model is largely acceptable.

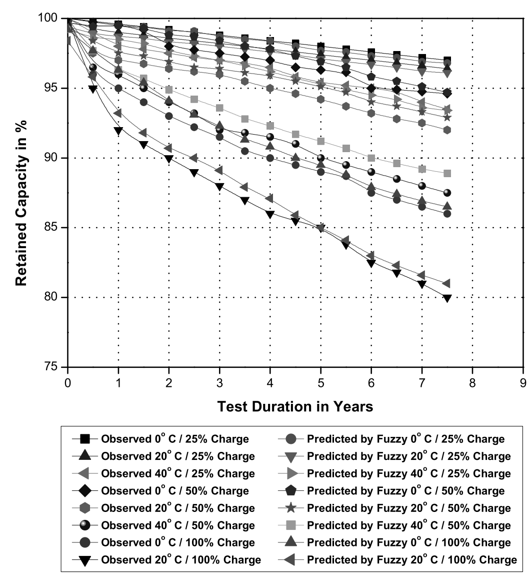

Fig.6. Observed and Predicted values of Retained capacity by Fuzzy results .

9. Results From ANN Model

Figure 7 shows retained capacity estimation using ANN model at various states of charge at different temperatures over seven and half years of calendar life. By visual inspection a good match is observed between the measured and predicted values.

It is found from the statistical analyses the correlation co-efficient is 0.9862, AAPE is 0.490% and the co-efficient of variation is 0.0059. From the results it is found that the ANN model has the ability to predict more accurately the retained capacity throughout.

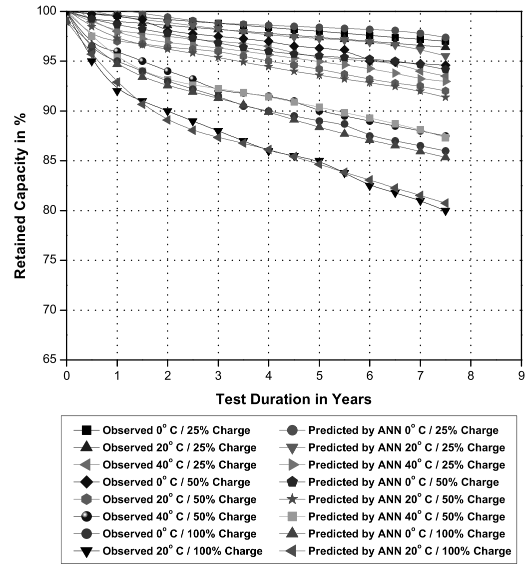

Fig.7. Observed and Predicted values of Retained capacity by ANN

10. Comparison of Fuzzy and ANN Models by Statistical Analysis and Bland Altman plot.

Comparison by Statistical Analysis

Fuzzy and ANN model designs have been compared to find the degree of prediction accuracy and generalization capability of the models. The same set of experimental data are used to test both the models to extract solid conclusion to find the better model by comparison.

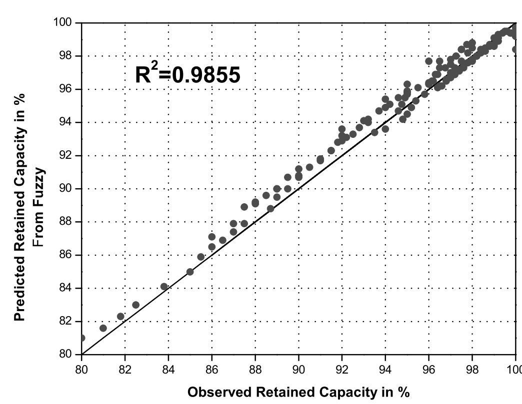

Fig.8. Comparison between Observed and Predicted values of Retained capacity by Fuzzy Model.

The predicted value of retained capacity are plotted against the experimental results. Accuracy of prediction in both the cases is estimated by 1:1 line which represents 100% accuracy as shown in figures 8 and 9. A visual inspection reveals that the ANN model is able to accurately predict throughout the range of calendar life than fuzzy model. From above discuss ANN model shows high degree of prediction accuracy and generation capacity in compare with fuzzy model.

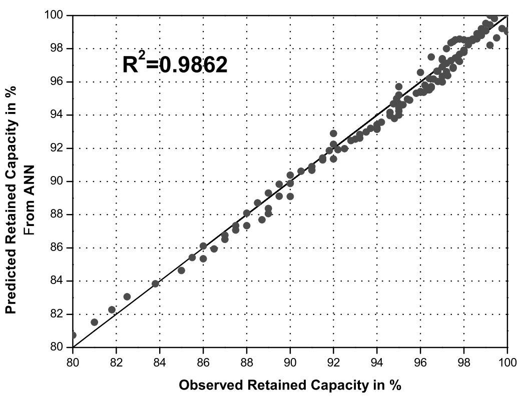

Fig.9. Comparison between Observed and Predicted values of Retained capacity by ANN Model

Bland Altman Plot comparison

Bland Altman plots for the comparison of observed and predicted values of retained capacity by both the models are given in figures 10 and 11. Bland Altman plot is deemed simple both to do and to interpret. It is considered to be a substitute for correlation and regression analysis. The X axis shows the mean value and Y axis represents the difference.

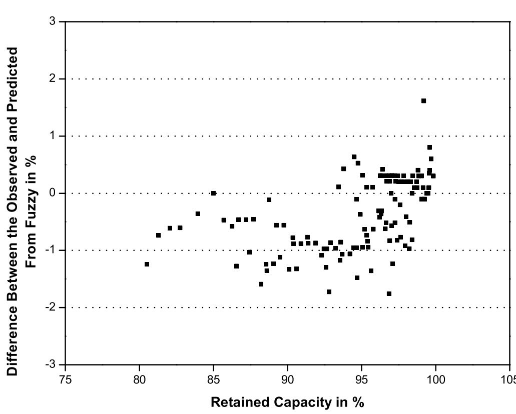

Fig.10. Bland Altman Plot for Observed and Predicted values of Retained capacity by Fuzzy Model.

From the Bland Altman plot it can be seen that variation between the observed and predicted retained capacity is with in ±2% for fuzzy model and ±1% for ANN model. This shows ANN models can predict to a greater accuracy and proves to be a better technique for battery modeling.

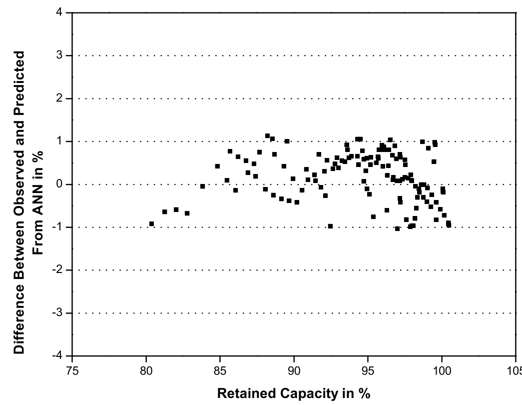

Fig.11. Bland Altman Plot for Observed and Predicted values of Retained capacity by ANN Model.

11. Prediction By Fuzzy And ANN Models

The retained capacity under conditions for which the test data sets are not available is also required to be predicted. This is to study the lithium-ion battery behavior at various state of charge at different temperatures and calendar life.

The range of input parameters settings for which the tests are not conducted is listed in Table 2. These input parameters are utilized to predict the retained capacity by the two models using experimental results. These predictions are as shown in figures 15 and 16. It is observed that the fuzzy model shows higher deviation at 40ºC and 100% state of charge compared to ANN model.

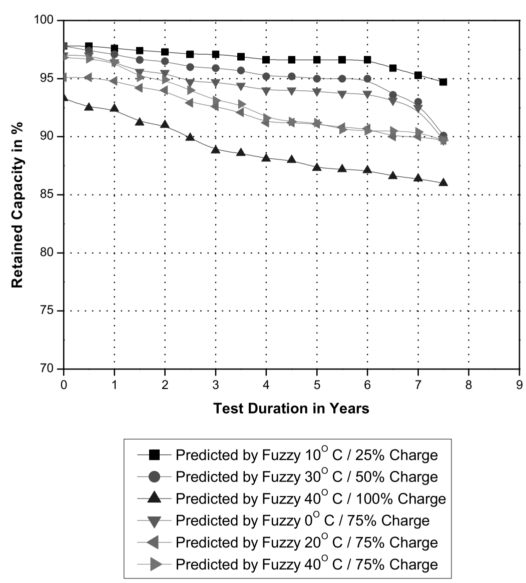

Fig.12. Predicted values of Retained capacity by Fuzzy Model for the inputs for which the tests are not conducted.

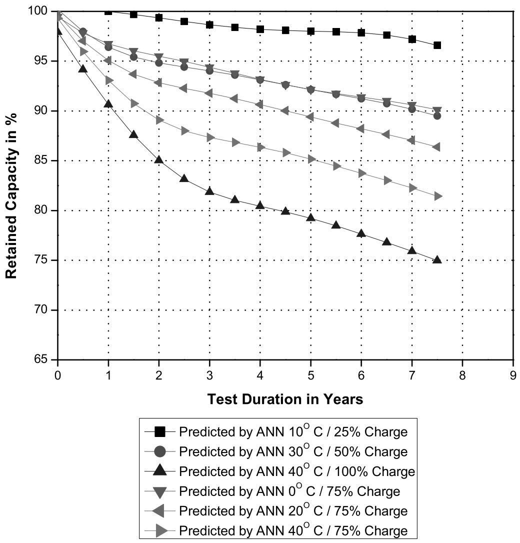

Fig.13. Predicted values of Retained capacity by ANN Model for the inputs for which the tests are not conducted.

Temperature	State of Charge
10º C	25%
30º C	50%
40º C	100%
0º C	75%
20º C	75%
40º C	75%

Table.2. Predicted range of parameters.

12. Extrapolation by Fuzzy and ANN models

Extrapolation capability of both the models for the prediction of retained capacity is very important to reduce the real time testing. In this paper fuzzy and ANN models are designed with the experimental results of four years storage period and this models are used to predict the retained capacity for seven and half years. This models has been presented with the data inputs for seven and half year storage period. The predicted values by this models are compared with the experimental results obtained for seven and half years to extract more solid conclusion to find the better model for extrapolation.

Fuzzy model has been designed with the same configuration as previously stated designed model for seven and half years except the number of fuzzy rules is 42 instead of 65. This model is tested with the input data for seven and half years and the graph between the prediction and the experimental results for seven and half year is plotted as shown in figure 14.

The statistical analyses by comparison has been made with drawing 1:1 line as shown in Figure 15. The correlation coefficient found to be 0.9292 the AAPE is 0.744% and the coefficient of variation is 0.0110. From the Bland Altman plot in figure 16, it is observed that almost for the entire range of values the error of prediction by fuzzy model is ±6%.

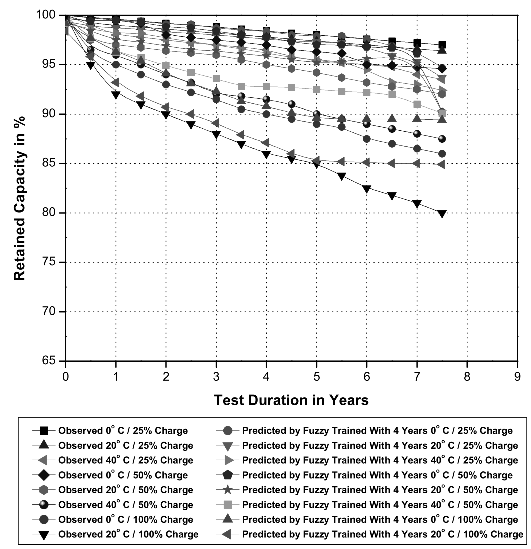

Fig.14. Observed and predicted values of retained capacity for seven and half year by fuzzy model designed with the four years of experimental results.

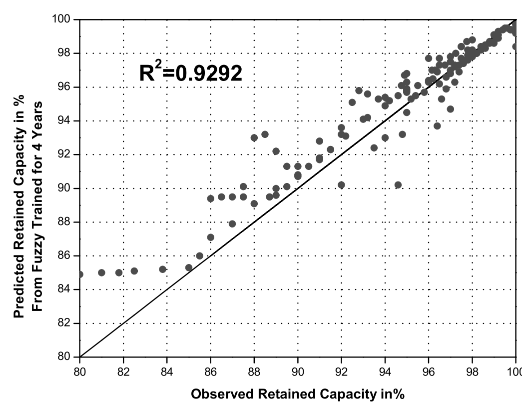

Fig.15. Comparison between observed and predicted values of retained capacity for seven and half year by fuzzy model designed with the four years of experimental results.

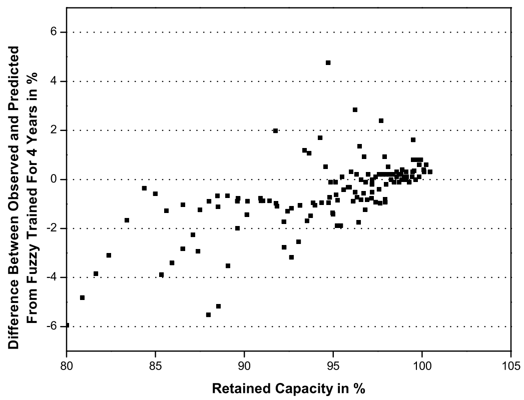

Fig 16. Bland Altman plot for observed and predicted values of retained capacity for seven and half year by fuzzy model designed with four years of experimental results.

The ANN has been trained with 72 data set obtained from experimental results for four years. The ANN model is designed with the same configuration as earlier designed network to predict the retained capacity for seven and half years. The network has been trained for error target of 0.5%. This trained network with four year experimental results is presented with the inputs to predict the retained capacity for seven and half years. The prediction by ANN model and experimental results has been plotted as shown in figure 17.

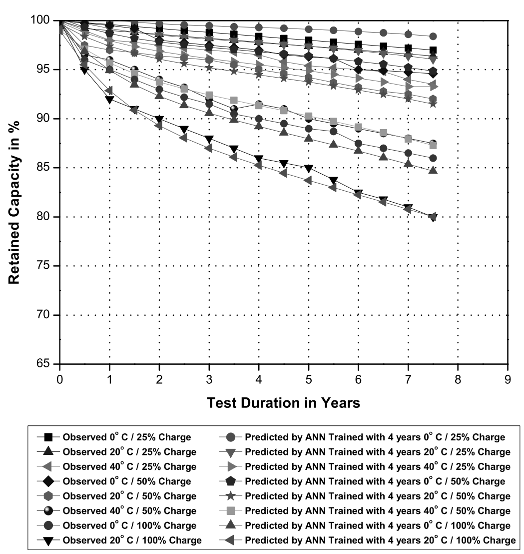

Fig 17. Observed and predicted values of retained capacity for seven and half year by ANN model trained with four years of experimental result.

The statistical analysis is made by drawing 1:1 line as shown in figure 18 to derive the ability of extrapolation by ANN .The correlation coefficient is 0.9854 with AAPE of 0.519% and the coefficient variation is 0.0064. Bland Altman plot for ANN model shown in figure 19 reveals that the variation for all range of value is less than ± 1.5%. From the above comparison between the Fuzzy and ANN model it is observed the ANN model proves to have excellent extrapolation capability .

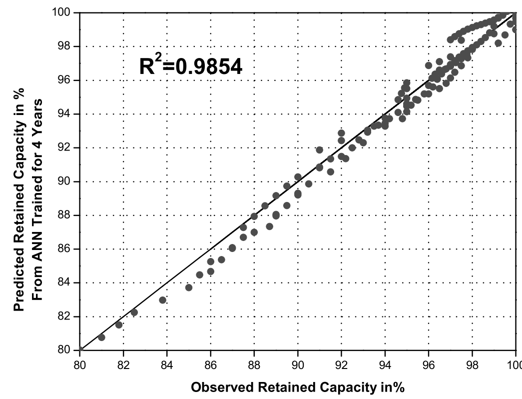

Fig 18. Comparison between the observed and predicted values of retained capacity for seven and half year by ANN model trained with four years of experimental result.

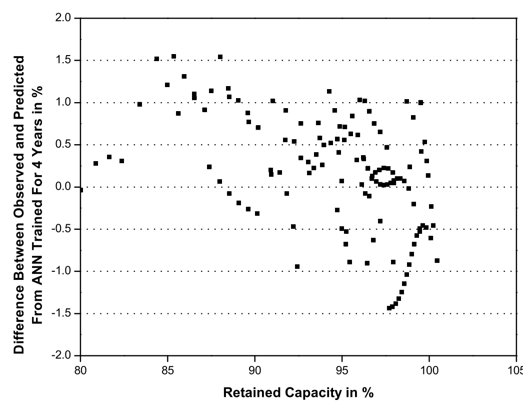

Fig 19 Bland Altman Plot for observed and predicted values of retained capacity for seven and half year by ANN model trained with four years of experimental result.

13. Conclusion

The fuzzy and ANN models presented in this paper show encouraging results for prediction of the retained capacity at various state of charge levels for life cycle. Both the models are able to predict more accurately over the test data set. It proves the capability of the Fuzzy and ANN approaches to model non linear complex systems such as batteries. It is interesting to note that ANN has excellent extrapolation capability in battery modeling. Both the techniques have shown encouraging results for lithium-ion battery modeling. From the above study it is concluded that state of charge influences the retained capacity of lithium-ion batteries.

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