Advanced Battery Management System using MATLAB/Simulink

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***Abstract*—A battery management system (BMS) is a system that manages a rechargeable battery (cell or battery pack), by protecting the battery to operate beyond its safe limits and monitoring its state of charge (SoC) & state of health (SoH). BMS has been the essential integral part of hybrid electrical vehicles (HEVs) & electrical vehicles (EVs). BMS provides safety to the system and user with run time monitoring of battery for any critical hazarder conditions. In the present work, design & simulation of BMS for EVs is presented. The entire model of BMS & all other functional blocks of BMS are implemented in Simulink toolbox of MATLAB R2012a. The BMS presented in this research paper includes Neural Network Controller (NNC), Fuzzy Logic Controller (FLC) & Statistical Model. The battery parameters required to design and simulate the BMS are extracted from the experimental results and incorporated in the model. The Neuro-Fuzzy approach is used to model the electrochemical behavior of the Lead-acid battery (selected for case study) then used to estimate the SoC. The Statistical model is used to address battery's SoH. Battery cycle test results have been used for initial model design, Neural Network training and later; it is transferred to the design & simulation of BMS using Simulink. The simulation results are validated by experimental results and MATLAB/Simulink simulation. This model provides more than 97% accuracy in SoC and reasonably accurate SoH.**

Keywords*— *EVs; SoC; SoH; BMS; NNC; FLC.

I. Introduction

Batteries are widely used as the most common electrical energy storage device in vehicles as a replacement of traditional fuel. The capacity of battery is gradually reduced due to corrosion, passivation, out gassing, decomposition of materials and morphological changes on electrode surface during its operation, when it is subjected to a load or a source. Also, the battery weakening process can be enhanced when the battery is subjected to operate beyond the specified safe operating conditions. The safe operation and long life of a battery depend on the current delivery during charging and discharging modes within the specified limit under all specified temperature conditions. The safe operation of battery cannot be estimated only by direct measurements as it also depends on the present state of the battery. The battery state is used to estimate the expected lifetime of the battery and can simply be described by two parameters: SoC and SoH. SoC is interpreted as a present charged state that mostly depends on current in & out and its initial charge condition of a battery at given temperature. SoH is a 'measure' that reflects the aging of a battery and its ability to deliver the specified performance compared to a fresh battery.

Battery Monitoring means keeping an eye on the key operational parameters during charging and discharging. Electrical key parameters are voltage, current, battery internal resistance and ambient temperature during cycles [1]. SoC & SoH indications provide protection by generating alarms or visual indications for any normal malfunctioning in the system. Smooth functioning of heavy mobile systems depends on the accurate SoC and SoH monitoring. The monitoring is addressed by an independent system known as battery management system. A general BMS architecture is presented and the function of each block is given in Ref. [2]. An effective BMS can protect the battery from damage, predict battery life, and maintain battery operation for offering high precision and perfection [3]. A few BMS for different battery packs which are now commercially available are detailed in Ref. [4-6]. A BMS for LiFePO4 battery is presented in Ref. [7]. A Modular Battery Management System for HEVs is presented in Ref. [8].

The BMS presented in this research paper is designed and simulated using the experimentally extracted parameters of the lead acid battery. In the present work, SoC is estimated using the Neuro-Fuzzy Approach, in addition multivariate linear Regression Model is used for estimating SoH [9]. The NNC is simulated & trained on the collected data set of lead acid battery using NNTOOL and transferred to Simulink. If-then rules of fuzzy modelling are defined to create the linguistic results. FLC is imported in Simulink. Regression Model is structured in Simulink by using different mathematical blocks.

The paper is organized as follows. The proposed advanced BMS is presented in section II including adopted SoC & SoH algorithms and their Simulink implementation. Further the MATLAB/Simulink simulation results are discussed in section III followed by conclusion remarks in section IV.

II. Advanced Battery Management System

The proposed structure of advanced BMS is shown in Fig. 1. The block diagram of the BMS is facilitated with the following blocks:-

- Battery Input Parameters Extraction Block
- NNC

- FLC
- Data Storage Read/Write Block
- Statistical Model
- Output Module

NNC and FLC together operate as SoC determination block of BMS. SoH determination block of BMS is a Statistical Model.

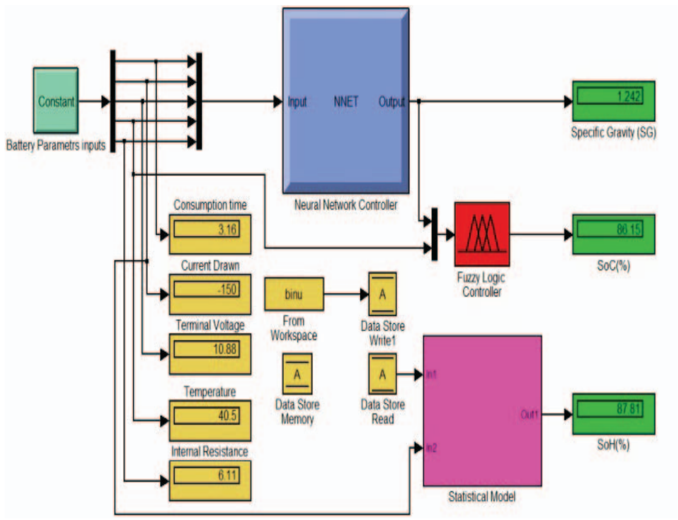


Fig. 1. Proposed structure of Battery Management System

The detailed descriptions of each block of proposed BMS are discussed below:-

A. Input Parameters Extraction

The selection of parameters and their data collection are big challenges in any kind of BMS design. We are referring pervious work of our research group where, our colleagues have collected data through laboratory based circuits- Bitrode battery test system and Agilent impedance measurement system at Exide Industries Ltd, R&D Lab, Kolkata, India for extracting the following five electrical parameters of a 12V lead acid battery MF40sv:- 1) Consumption Time 2) Current Drawn 3) Terminal Voltage 4) Temperature 5) Internal Resistance. Results given in Ref. [10] proves that NNC design with preferred above five input parameters gives greater than 99% accuracy for Specific Gravity (SG) measurement, whereas the accuracy reduces to less than 90% with four parameters (Current Drawn, Terminal Voltage, Temperature, Internal Resistance) and falls down to less than 60% when only three parameters (Current Drawn, Terminal Voltage, Temperature) are employed, leading to the decision that all five parameters are essential for accurate BMS design. The measurements were carried out after simulation of operation of car in the lab separately for Slow Discharge (SD) and Real Cranking (RC) at different temperatures (0^0C, 27^0C & 47^0C), different state of charge (100%, 75% & 50%) and for different age of battery (fresh battery, one year old, two year old), as shown in activity chart Fig. 2.

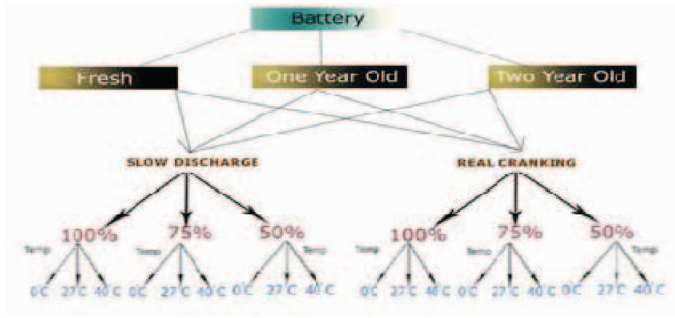


Fig. 2. Activity chart for data collection

Our previous research group also implemented the model into an instrumentation board for measuring & scaling of all the five parameters of battery as shown in Fig. 3. The inbuilt microcontroller on the instrumentation board runs the NNC & FLC algorithms.

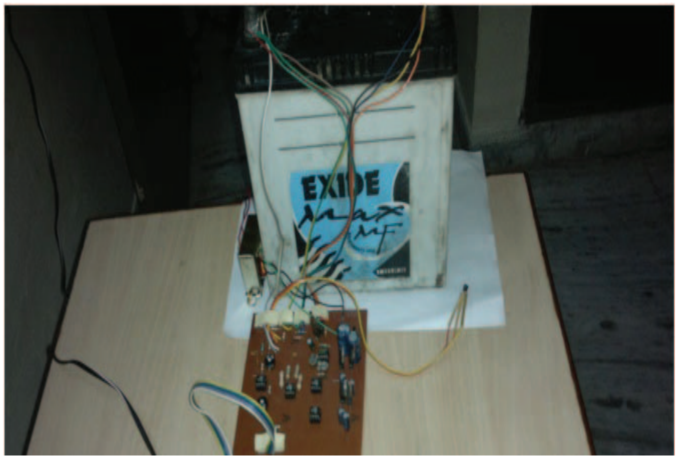


Fig. 3. Instrumentation Board for extracting battery parameters

B. Neural Network Controller

The NNC is facilitated with Artificial Neural Networks (ANN) model which gives Specific Gravity (SG) output in response to stimuli of battery parameters. The NNC algorithm and its Simulink implementation are discussed in the following sections.

1) Algorithm for SG determination

One of the key parameters of battery operation is the specific gravity of the electrolyte. ANN is used in this research to simulate the discharging process of a battery and to predict the specific gravity of electrolyte using all five input parameters [10].

2) Simulink Implementation

In the present research, the NNC block of proposed BMS in Fig. 1 is facilitated with the algorithm of SG determination/ANN architecture. The detailed Simulink Model of NNC is shown in Fig. 4.

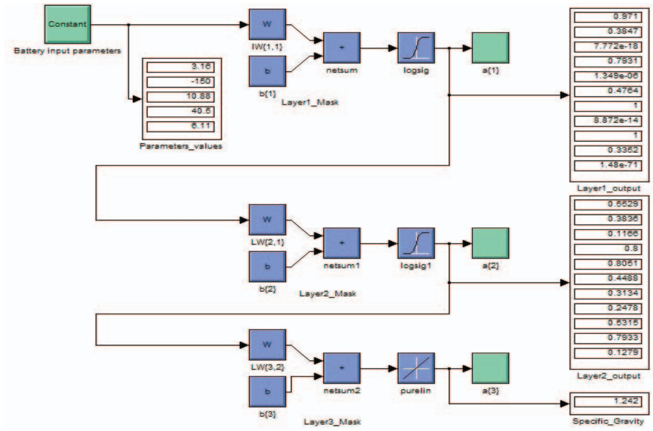


Fig. 4. Simulink Model of Neural Network Controller

NNC is multilayered architecture that consists of three cascading layers. The selected five battery parameters are fed as inputs to the controller using constant value parameter block (Battery input parameters). The inputs of each layer are initially processed through the *dotprod* block which is used to evaluate dotprod function between the layer's inputs and layer's weights. The weights of layer1, layer2 & layer3 are defined inside the blocks IW{1,1}, LW{2,1} & LW{3,2} respectively. The constant value parameter blocks b{1}, b{2} & b{3}are incorporated in controller to hold the biases values for layer1, layer2 & layer3 respectively. The blocks *netsum* is a net input function block and used to predict the net inputs for layer1, layer2 & layer3 respectively by combining their weighted inputs & biases. The blocks *logsig* & *logsig1* of controller are representing the *Log-sigmoid transfer function block* and block *purelin* is representing the l*inear transfer function block.* These blocks are used to calculate the required output of each respective layer from their net inputs. The parameter blocks a{1} & a{2} are the vectors of eleven constant values for the eleven neurons of Layer1 & Layer2 respectively. The predicted output of NNC that is specific gravity, is observed by the constant value parameter block a{3}.

The model in Fig. 4 calculates the specific gravity of 12V Lead-acid battery equals to 1.242 for 150A discharge for 3.16 minutes at 40.5^{0}C temperature. The battery terminal voltage drops to 10.88 volts from its initial voltage and internal resistance increases to 6.11 ohms due to discharge.

C. Fuzzy Logic Controller

In the present research, FLC is designed to estimate the SoC of lead acid battery. The FLC algorithm and its Simulink implementation are discussed in the following sections.

1) Algorithm for SoC determination

The Neuro-Fuzzy Approach is adopted for SoC estimation in which the nonlinear adoptive-learning capability of ANN is used to simulate the discharging process of a battery which is translated linguistically using fuzzy logic to indicate the charged state of the battery [11]. In the reference paper [12], FLC is employed for the purpose of transforming the relationship between input Specific Gravity (NNC output) and the battery temperature with the SoC to a linguistic term depending on the 35 rules of fuzzy modeling. If-then rules of Fuzzy Modeling are defined in table 1 to specify the SoC of the battery.

Table 1: The Fuzzy Rule Base for %SoC

Temperature \ Specific Gravity	VVL	VL	Low	medium	high	VH	VVH
Very Low	Flat	Flat	Flat	Flat	Flat	<Half	<Half
Low	Flat	Flat	Flat	<Half	<Half	Half	>Half
Medium	Flat	Flat	Flat	Half	>Half	>Half	>Half
High	Flat	<Half	<Half	Half	>Half	>Half	Full
Very High	<Half	<Half	<Half	Half	>Half	Full	Full

2) Simulink Implementation

In the present research, the implementation of FLC is done using MATLAB's Fuzzy Logic Toolbox and then translated to Simulink as shown in Fig. 5.

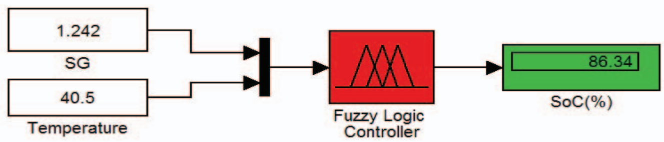


Fig. 5. Simulink Model of Fuzzy Logic Controller

The specific gravity and temperature online inputs are applied to FLC, algorithm runs and predict the SoC. Defuzzification block is used within the FLC for interpreting the membership degrees of the fuzzy sets into crisp value. Fig. 5 shows a combined block of fuzzification & defuzzyfication to provide crisp values of SoC by superimposing If-then rules. Fuzzy Inference System (FIS) incorporated in FLC is shown in Fig. 6.

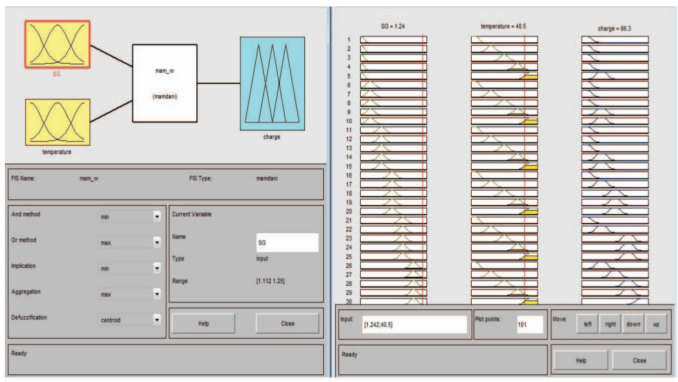


Fig. 6. Fuzzy Inference indicating full charged status of battery

Here, it is noticed that SoC results of Simulink model of FLC in Fig. 5 and fuzzy inference system in Fig. 6 are similar.

D. Statistical Model

In the present research, the statistical model of SoH is implemented by Simulink. The cause of battery health deterioration is the effect of aging on the grid, electrodes, contacts, corrosion and charging /discharging cycles. The algorithm for SoH estimation and its Simulink implementation are discussed in the following sections.

1) Algorithm for SoH determination

The SoH determination technique using multivariate linear regression [11] on the aging effect and the on-time consumption of the battery is selected for implementation. The formula obtained for estimating SoH after applying the multiple regression technique is given as:

$$SoH = 1.0043 + 0.0088(TT \times C) + 3.8925\, m(SG) + 0.2444 m'(OCV) - 0.0863 m''(IR) \qquad (1)$$

Where TT is the run-time of the battery and C is the discharge rate. TT × C gives the ampere-hour consumption of the battery and m (SG), m' (OCV) and m'' (IR) are slopes of specific gravity, terminal voltage and internal resistance respectively whose values are calculated in Ref. [12]. SoH is representing the used life of battery. The expected battery life is estimated by the following formula:

$$\text{Expected Battery Life (\%)} = 100 - \text{Used Life (SoH)} \qquad (2)$$

2) Simulink Implementation

The multivariate linear Regression Model described in equations (1) & (2) for battery SoH estimation is implemented in statistical Model block of proposed BMS in Fig. 1 and its detailed structure is shown in Fig. 7.

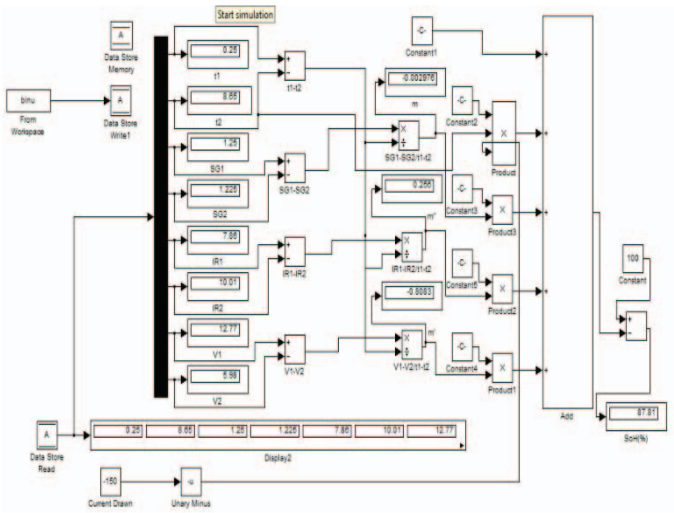


Fig. 7. Simulink Implementation of statistical model

The constant parameters are fed to the Statistical model by using six constant parameters blocks. The value of the discharge current 'C' is fetched from the data input as a real time data from the proposed structure of BMS as shown in Fig. 1. The sum blocks and product blocks are used to determine the required slops m, m' & m'' using the real time data of SG, OCV & IR. For testing purposes, the required data for slops calculation and the value of TT are saved in memory and called during the implementation of statistical model to provide SOH of a lead-acid battery as per equation (1). The final output of Statistical Model comes out in the percentage using equation (2).

III. MATLAB/SIMULINK SIMULATION

Initially, the ANN is designed, trained and simulated using nntool of MATLAB. Then NNC is design in Simulink in which the ANN algorithm is implemented. The comparison between the output of NNC (i.e SG_Observed_ANN) and the experimentally measured SG of lead-acid battery (i.e. SG_experimental_Exide) is shown in Fig. 8. The value of the sum of squares of error (SSE) is 0.0004989 and R-square is 0.999. Results in the Fig. 8 verify the values of SSE & residual.

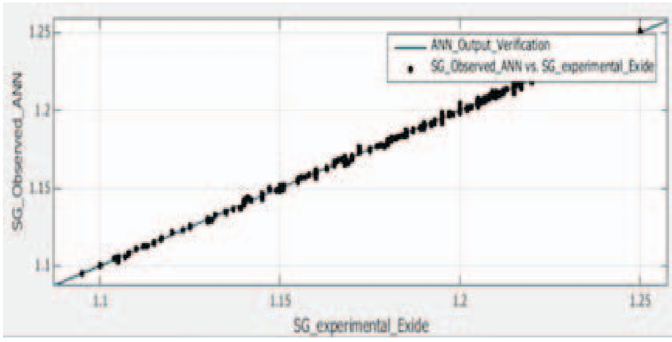


Fig. 8. SG of ANN versus SG experimental

This linear plot proves that NNC Simulink model is accurately designed as it measured the expected values of experimental SG and values of SSE & R-square also proves 99.9% accuracy of our model. The variations in the estimated SoC of advanced BMS with the increase in SG & temperatures compensated at 0^0C, 27^0C & 40^0C are shown in Fig. 9.

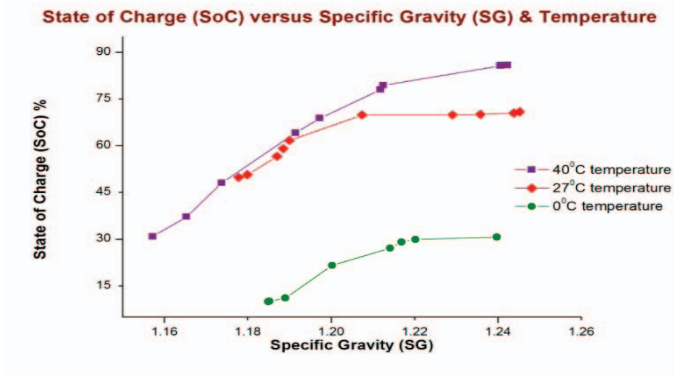
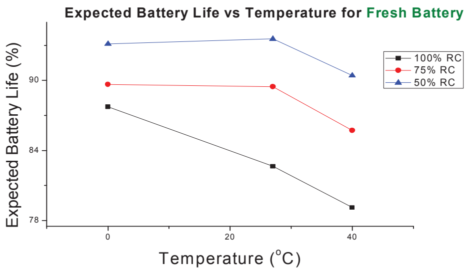


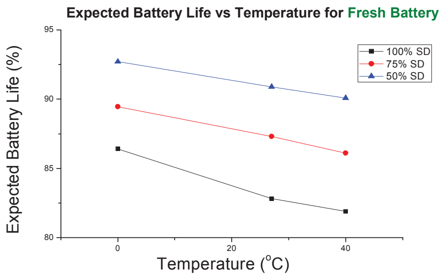
Fig. 9. SoC versus SG & Temperature

It is observed that SoC is high at higher Specific Gravity and also increases with increase in temperature (verified from [13], [14]). The relation between SoC & SG is not linear at different temperatures due to the effect of increase in temperature on electrochemical reactions and out gassing or hydrogen gas generations. In addition, Fig. 9 does not show 100% of SoC even at 1.24 service specific gravity that means battery suffers from capacity loss and its operation varies with temperature. The capacity loss should be compensated for temperature variations.

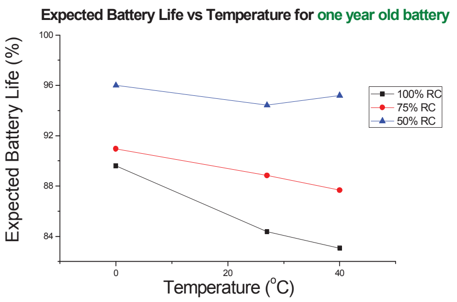
In Fig. 10, the graphical representations of the expected percentage battery life with temperature at different ages of battery (fresh, one year old & two year old) for RC & SD operations of a car are shown. The Fig. 10 (A), (C) & (E) represent the RC operation of a car and Fig. 10 (B), (D) & (F) represents the SD operation of a car.



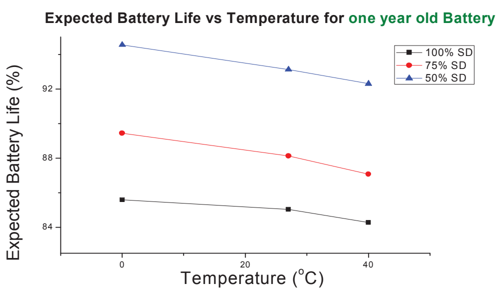
(A)



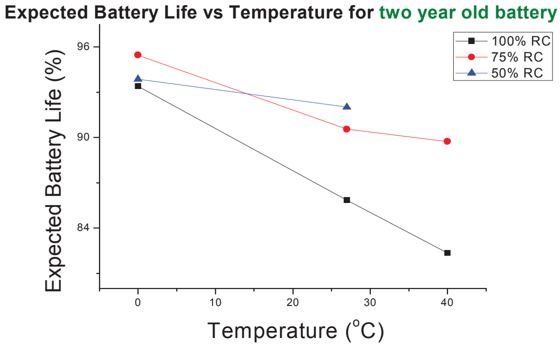
(B)



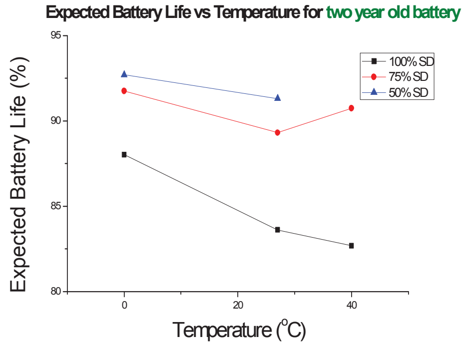
(C)



(D)



(E)



(F)

Fig. 10. Expected Battery life versus Temperature for different aging of battery for both RC & SD operations

It is observed here that battery life is reducing with increase in temperature (verified from [14]) and also battery is degrading as it is being old.

IV. Conclusion

In this research paper, it is concluded that MATLAB/Simulink model implementing the Battery Management System is very efficient approach to indicate the battery state SoC & SoH. There are lots of methods existing in market for SoC & SoH determination. In the presented paper, the Neuro-Fuzzy and Statistical model are re-simulated with Simulink to compare the two MATLAB tools and for connecting the Simulink model to HDL coder for chip design of BMS. It can be seen by MATLAB/Simulink simulation results that a Neuro-Fuzzy Approach & Statistical Model have high degree of confidence for control strategy & implementation of a BMS. The designed Simulink model will be convenient for developing FPGA based BMS. FPGA based BMS has advantages over other existing BMS because of low NRE cost, low power consumption, high speed of operation, large reconfigurable logic, large data storage capacity and hence better performance.

References

[1] Vinal, G.W., "*Storage Battery*", John Wiley and Sons, New York, IVth edition, pp.130-336, 1924-1955.

[2] Valer Pop, HJ Bergveld "Battery Management System Accurate State-of-Charge Indication for Battery Powered Applications" Philips Research Book Series Volume 9 Chapter 1, Springer Nederland 2008.

[3] C. Chen, K.L. Man "Design and Realization of a Smart Battery Management System" International multiconference of engineers and computer scientists volume II, Hong Kong 2012.

[4] EV Hybrid Vehicle Electronic, Extend Computer and Instrument, http://www.extendcomputer.com/html/ev_hybrid.html.

[5] Smart Guard Battery Control System, Aerovironment, Inc., http://www.aerovironment.com.

[6] BatOpt Battery management System, AC Propulsion Inc., http://www.acpropulsion.com/products/Battery_mgt.html.

[7] B.P.DIVAKAR, H.J.WU, J. XU "Battery Management System and Control Strategy for Hybrid and Electric Vehicle" 3rd International Conference on Power Electronics Systems and Applications 2009.

[8] Thomas Stuart, Fang Fang "A Modular Battery Management System for HEVs" University of Toledo 2002.

[9] Neeta Khare, Rekha Govil "Modeling Automotive Battery Diagnostics" Power Electronics Technology, March 2008.

[10] Neeta Khare, Rekha Govil "A Battery Storage System for Fault Tolerance" IEEE, 2007.

[11] Neeta Khare, Rekha Govil, and Surendra Kumar Mittal, "A Process of determining State of Charge and State of Health of a Battery", Indian Patent, 813/KOL/2005.

[12] Neeta Khare, Shalini Chandra and Rekha Govil "Statistical modeling of SoH of an automotive battery for online Indication" IEEE, 2008.

[13] Rolls Battery Engineering, North America http://www.rolls-battery.com/content/technical-downloads?q=node/51.

[14] BDI Inc. http://cms.cdnrg.com/images/uploads/downloads/files/Temperature_Effec ts.pdf.