

**INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH
TECHNOLOGY****FPGA DESIGN SCHEME FOR BATTERY SOC & SOH ALGORITHMS FOR
ADVANCED BMS****Bijender Kumar^{*1}, Neeta Khare², P.K. Chaturvedi³**^{*1}Electronics Engineering Department, Banasthali University, Banasthali, Rajasthan-304022, INDIA²The Energy Storage Research Centre ESReC, BFH, Switzerland³Electronics & Communication Engineering, SRM University, Ghaziabad, U.P., INDIA

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ABSTRACT

Batteries are primary source of clean energy for various applications such as transportation, grid storage & mobile systems. In case of transportation, the effective use of existing battery technology in Electrical Vehicles (EVs) & Hybrid Electrical Vehicles (HEVs) remains a challenge because of inaccurate battery state-of-charge (SoC) & state-of-health (SoH) models. A battery's stored energy & its performance are difficult to infer from electrically measured parameters of a battery. This research paper aims at describing different battery technologies used in transportation applications & their performance comparison, comparison of different SoC & SoH indication algorithms and commercially available Battery Management System (BMS). The goal of all the presented SoC & SoH indication algorithms is to select an accurate algorithm and to design an advanced BMS capable of providing an accurate indication of battery state. Further, this research paper describes the Neuro-Fuzzy & statistical controllers to be incorporated in Advanced BMS for accurate monitoring of battery's SoC & SoH respectively. In Neuro-Fuzzy approach, a neural network is used to model a nonlinear electrochemical behavior of the Lead-acid battery. In statistical model, a regression method is employed to predict the SoH. This paper also describes MATLAB simulation of artificial neural network (ANN) model selected for Advanced BMS design & the Field Programmable Gate Array (FPGA) design scheme for BMS implementation. The SoC and SoH estimation results of lead-acid battery using Simulink and RTL (register transfer level) models are also summarized in this paper. FPGA implementation would provide the chip design to determine accurate SoC & SoH of the lead acid battery.

KEYWORDS: EVs, HEVs, SoC, SoH, ANN, BMS, FPGA, HDL.**I. INTRODUCTION**

Batteries are the true power behind everyday life because they are most common sources of electrical energy storage in all most every power back-up application. They are very popularly used in the systems like - cars, boats, public transportation as hybrid source or recharge plug-in power source. With the increased need of mobility, people moved to the portable power storage - first for wheeled applications, then for portable and finally nowadays wearable use. As the usage of the battery increases, an accurate monitoring of battery state becomes more relevant. The internal state information of the battery is one of the most important factors to protect the system from failure. In recent example of Boeing 787 [1] a fire accident, an airline have used lithium-ion batteries to deliver power for its energy-hungry electrical systems. After the analysis of fire accident in jet, it was found that electrolytes, a flammable battery fluid, had leaked from main lithium-ion battery pack and entire system got damaged. A series of fire incidents has also happened with the Samsung galaxy 7 smart phones. A few sources has blamed to packaging of the Li-ion battery in the smart phone which caused short circuit of separator and led to thermal runaway.

Obviously, detecting in-time battery failures and determination of the battery state become necessary for system and user safety. Battery state is an estimated life of the battery and can be described by two parameters: SoC and SoH. SoC is interpreted as a present charged state of a battery which is mostly determined by electrical parameters of a battery. Poor SoC of a battery indicates the need for battery charging. By contrast, SoH of a

battery is indicative of its need for conditioning to restore its power delivery capability or replacement. The SoC & SoH provides protection by generating alarms or visual indications for any malfunctioning in the system. On the other hand, Battery Monitoring means keeping a check on the key operational parameters during charging and discharging such as voltage, current, battery internal resistance, ambient & cell temperatures and charging/discharging cycles [2].

Nowadays, various battery technologies are commercially available in the market. The most common battery parameters which specify the performance of rechargeable battery systems are following:

- 1) Nominal operating voltage
- 2) Energy density
- 3) Specific energy
- 4) Self discharge rate
- 5) Cycle life
- 6) Temperature range

A comparative analysis of main characteristics of different battery system is summarised in the table 1 [3].

Table 1. Characteristics analysis of the most important rechargeable battery systems

Battery system (Parameters)	NiCd	NiMH	Li-ion (FePO ₄)	Lead Acid	ZnBr	NaS
Nominal operating voltage (V)	1.2	1.2	3.6	2	1.8	2
Energy density (W h l ⁻¹)	90–150	160–310	200–280	60-75	15.7–39	151
Specific energy (W h kg ⁻¹)	30–60	50–90	90–115	30-40	34.4–54	150-760
Self-discharge rate (%/month)	10–20	20–30	5–10	3-4	7.2	No
Cycle life	300–700	300–600	500–1000	500-800	>2000	4500
Temperature range (°C)	–20–50	–20–50	–20–50	–20–55	0-45	300-350
Commercialization	1956	1990	1992	1881	1970	2002

The battery parameters given in table 1 are highly dependent on the electrochemical reactions between species. These reactions involve electric charges moving between the electrodes and the electrolyte. The battery performance degrades due to variations in parameters/reactions with the battery usage & aging at different operating conditions. An optimum usage of the battery demands on an accurate BMS. Many different commercialised BMS products for various application platforms and few chip sets for battery management are reviewed here. A literature review has revealed that BMSs are still in a premature stage. Neither the standard definition of SoC and SoH exist, nor do BMS designs follow any common standard safety, charging methodology and communication protocols. Even if state-of-the-art algorithms and monitoring methods were developed and applied in EVs and HEVs, the reliability of BMS would still make end users suspicious. This research paper summarizes the main features and general block diagram of a BMS followed by a survey on different diagnostic & prognostic methods of SoC & SoH determination. Further the commercial BMS ICs deploying different SoC & SoH algorithms are overviewed section 3. The design methodology used for FPGA-based BMS chip implementation is presented in section 4. Finally, this paper closes with the explanation of MATLAB and RTL simulation results, followed by concluding remarks.

The scope of work covers the development of a BMS chip for an accurate estimation of SoC & SoH of the lead-acid battery. The proposed BMS design can be easily extended to different battery technologies also. In this research paper, we have taken lead-acid battery as case study because of the following reasons:-

- 1) The lead acid chemistry is extremely robust & well-understood technology.
- 2) Lead acid batteries function well in a broad range of temperatures and environmental conditions.

- 3) Lead acid batteries are inexpensive, simple to manufacture, mature, reliable and require low maintenance. However it has less cycle life and low energy density.
- 4) Industries are progressing in remodeling lead-acid batteries for higher cycle life by combining them with super capacitor and other hybrid electrodes for stationary and mobile applications.

Besides automotive applications, lead-acid battery has proved its importance in off-time/stand alone applications. Lead acid batteries are the energy storage workhorse and at present, most ubiquitous form of energy storage in the world. The paper has included a description of Neuro-Fuzzy approach for SoC indication and statistical model for SoH indication from our previous work [4]. These models are incorporated in our proposed BMS chip implementation. The proposed BMS uses the battery parameters as inputs to the Neuro-Fuzzy & Statistical controllers for estimating SoC & SoH respectively. ANN is designed, simulated & trained on the collected data set for lead acid battery. If-then rules of fuzzy modelling are defined to create the linguistic terms for SoC results. ANN & fuzzy rules are deployed in Neuro-Fuzzy controller for SoC estimation. Further, the slopes of the selected battery parameters are used to develop a regression formula to estimate SoH of battery. Statistical controller computes the regression formula for SoH estimation. Our proposed BMS chip implementation is expected to estimate accurate SoC & SoH of the lead acid battery

II. BATTERY MANAGEMENT SYSTEM

BMS is used to protect the battery from damage, predict battery life, and maintain the battery operation to retain the efficiency high [5]. BMS ensures the optimum use of the battery energy in-powering the portable product and provide safety to system and user. This is achieved by monitoring and controlling the charging and discharging processes of the battery. One or more of the following features should be included in BMS design:-

- 1) Charge control
- 2) Balancing the cell voltage/SoC among the pack
- 3) Battery capacity & efficiency calculations
- 4) Remaining run-time information
- 5) Battery life
- 6) Thermal profile
- 7) Prediction of battery failure
- 8) Safety & alarm indications etc

A general block diagram of a BMS is shown in figure 1 [6]. The power module (PM) charges the battery from the mains.

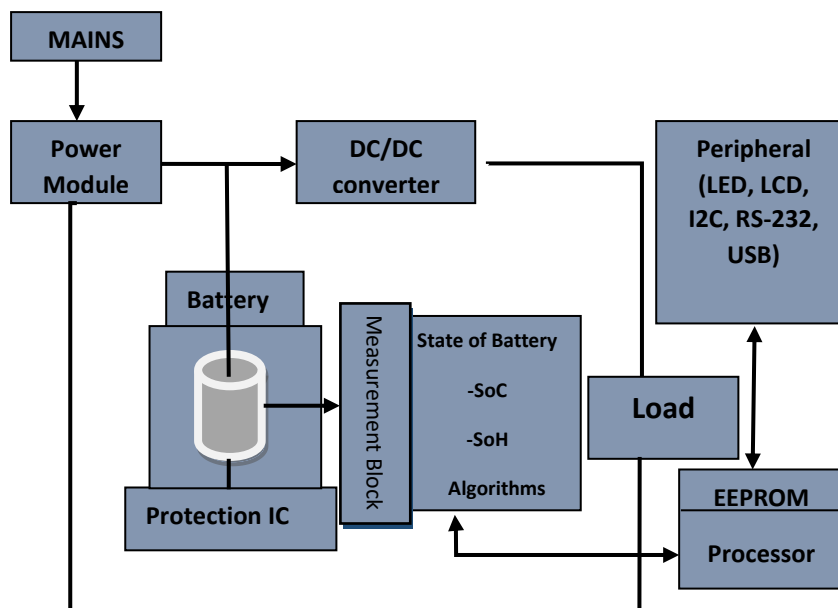


Figure 1: Block Diagram of Battery Management System

A protection Integrated Circuit (IC) connected in series with the battery indicates the unsafe condition of the battery. Protection IC specially deals with the over voltage protection, over current protection and thermal runaway. The measurement block captures battery parameters. All of these data are then used to estimate the

battery status in later stage. The dc/dc converter aggregates DC output of battery for compatibility with stringent load requirements. The processor runs the battery-management algorithm which includes SoC & SoH computation and displays the results on screen. I2C interface establishes communication between BMS and other devices.

The reliable, efficient and safe operation of rechargeable batteries requires monitoring, control and management. A core function of BMS is to provide an accurate estimation of SoC & SoH of batteries. This research paper describes most commonly used SoC & SoH estimation methods in the following sections.

2.1 SoC Indication Models

Various methods of SoC estimation exist in literature and their comparison analysis is overviewed in Table 2. It is apparent from table 2 that various tradeoffs exist between different SoC methods.

Table 2. Comparative analysis of different SoC indication methods

Sr. No.	Categories	Methods	Application Field	Merits	Demerits
I	Direct measurement method	Discharge Test [8]	Used for capacity measurement at the beginning of life	Easy to implement and accurate	Offline
II		Coulomb counting/ Book-keeping systems[11-14]	All battery system, most applications	Online, simple & easy to implement. Achieves high accuracy if initial value is corrected periodically	Accuracy depends on initial value; small errors could cause errors in all subsequent values. Requires high accuracy current sensors
III	Model based approaches----- Electrical & electrochemical models	Open circuit voltage [15]	Lead, lithium, Zn/Br	Easy to implement, most batteries have a defined relation between the OCV & SoC	Offline, but can be online if OCV is inferred from terminal voltage measurements or suitable models
IV		Impedance spectroscopy [16]	All battery systems	Real time prediction based on battery system impedance model, electrochemical model or behavior model	Difficult to implement, computational cumbersome, very specific to a battery technology
V		Kalman filters [17-28]	All battery system, PV, dynamic applications	Online, highly accurate because it's based on electrochemistry of battery	Very hard to implement, highly specific to the battery being used
VI	Adaptive & machine learning methods	Artificial Neural Networks [29]	All battery systems	Online, high adaptability to non-linear behavior of battery	Heavy computation, expensive to implement, dependent on training process
VII		Fuzzy logic [30]	All battery systems	Online, capable for non-linear modeling	Ask for large memory in real-world applications
VIII		Support Vector Machine [31]	All battery systems	Generic, good nonlinearity mapping	Ask for huge amount & quality of training data
IX		Neuro-Fuzzy Model [4]	All battery systems	Online, more accurate, high adaptability to non-linear behavior of battery, user friendly because of linguistic output	Large memory consumption, needs huge training data set of battery, heavy computation

irect measurements methods are the most reliable methods of SoC estimation. Measurements of battery charge are obtained by using a constant current to continuously discharge of the battery [7]. The remaining power is the product of the discharge current and the time. The measurements are performed as soon as the battery is connected. The discharged test method forces the battery to stop running, thus this method is not suitable for the moving electric car.

Most of SoC estimation methods define an electrical or electrochemical model from measurements of battery parameters such as terminal voltage, current, resistance and temperature. The model-based approaches for SoC estimation enable efficient and reliable integration of batteries in HEV power trains. In the model based methods, the additional information of the battery in the form of battery models is also used to compute SoC of the battery. The current and voltage measurement signals are provided as the feedback to form a closed loop estimation method, leading to more accurate SoC estimation. Electrochemical methods are considered more accurate [8]; however, they are hard to implement due to the complexity and requirement of large electrochemical parameters those are not easily available.

On the other hand, adaptive & machine learning methods introduce the advanced algorithms to estimate the SoC of the battery. These methods treat the battery as a black box to predict the non linear behavior [9]. However, they require a lot of offline training data to model the black box. Hence their accuracy is highly dependent on the training process, which makes them not robust to varied battery operating conditions. But the learning algorithms of these methods are once well trained; they provide more accurate SoC & SoH results.

The combination of the two or more methods, the hybrid model is also very common for SoC estimation such as book-keeping & Kalman filter [10] and ANN & fuzzy logic [4].

Note: We have selected the Neuro-Fuzzy model for SoC estimation in BMS chip implementation. In our proposed FPGA based BMS chip implementation (section-4), Neuro-Fuzzy model is implemented using Neuro-Fuzzy Controller for SoC estimation.

Neuro- Fuzzy Model

Artificial Neural Networks (ANN) is well known for simulating nonlinear physical processes. ANN coupled with fuzzy logic provides a powerful mechanism to linguistically translate the behaviour of a complex physical process. The nonlinear adoptive-learning capability of ANN is used here to simulate the discharging process of a battery which is translated linguistically using fuzzy logic to indicate the SoC of the battery in user friendly terms [4]. A schematic diagram of Neuro-Fuzzy model for SoC determination is shown in figure 2. Author has used ANN to simulate the discharge process of a battery by mapping of five online parameters of battery such as voltage, current, internal resistance, discharge duration and temperature onto the specific gravity (SG) of electrolyte. The SG of battery electrolyte has been known as accurate measures of SoC.

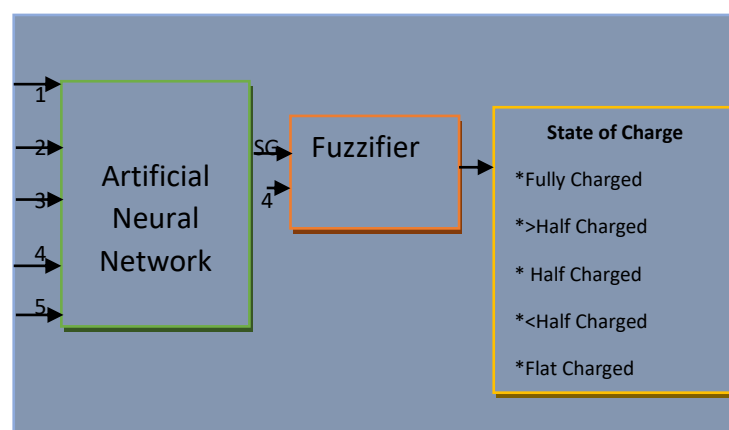


Figure2: A schematic diagram of Neuro-Fuzzy model for SoC determination

The SG and temperature are then mapped onto SoC of battery using Fuzzifier to represent results in linguistic terms such as Fully Charged, >Half Charged, Half Charged, <Half Charged and Flat Charged.

In the figure 2, the parameters 1-5 are the real-time inputs to the ANN to generate output in terms of SoC indications. These inputs are 1- Terminal voltage, 2- Current Drawn, 3- Internal Resistance, 4- Extracted

Temperature and 5- Consumption time. These parameters are directly measurable. The output Specific Gravity along with the battery temperature is used as input to a Fuzzifier to provide SoC in linguistic terms such as very high, high, half, low and very low. ANN model implemented in Neural Network Toolbox of MATLAB consists of the input layer (containing five inputs neurons), two hidden layers (containing eleven neurons each) and output layer (containing one neuron).

Author has described the simulation experiments performed with data collected on Exide car battery MF40sv used in Maruti Alto Car. In normal fuel automobile operations, battery bank supports the two modes i.e. Real Cranking and Slow Discharge (discharge due to electric load). The ANN is trained using combined sets of data for slow discharge and real cranking operations for different battery ages at various environment temperatures for various initial SoC conditions. The ANN is retrained in this research paper and generates an accuracy of 99.60%.

Author has also explained optimization on required input parameters, to obtain cost reduction in the design. The results are shown in the Table 3. ANN trained with five preferred parameters gives greater than 99% accuracy, whereas the accuracy reduces to less than 90% with four parameters and falls down to less than 60% when only three parameters are employed, leading to the conclusion that all five parameters are essential for better accuracy.

Table 3. Effect of input parameters on the accuracy of ANN output

Sr. No.	No. of inputs to ANN	Epochs	Surface Error	Accuracy at 1.240 Specific Gravity
I	Three 1,2,3	3075	0.584946	53.22%
II	Four 1,2,3,4	1298	0.133069	89.50%
III	Five 1,2,3,4,5	1481	0.0053373	99.60%

Fuzzifier is implemented in Fuzzy Toolbox of MATLAB. Fuzzy logic and 35 defined rule base are deployed in order to map SG and temperature onto SoC. If-then rules of Fuzzy controller are defined in the table 4 to determine the linguistic term of SoC of the battery. Here, SG is represented in linguistic terms such as VVL, VL, Low, medium, high, VH and VVH. The linguistic terms used for represent the temperature are Very Low, Low, Medium, High and Very High.

Table 4. Fuzzy Rule Base for linguistic variables of 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

2.2 SoH Indication Models

The SoH become a more complex parameter of a battery as there is no agreed definition of it. SoH indicates battery aging in terms of deterioration due to cycle life and calendar life. Various SoH estimation methods exist in literature and their comparison analysis are overviewed in Table 5.

Table 5. Comparative analysis of different SoH indication methods

Sr. No.	Catego-ries	Methods	Merits	Demerits
I	Durability model-based open-loop methods	Durability mechanism [32-33]	Comprehensive understanding	Complex, need accurate input parameters
II		Durability external characteristics [34-37]	Simple and easy to predict capacity fade and internal resistance increment	Based on a large number of experiments
III	Battery model-based parameter identification closed-loop method	Conventional resistance [38]	Simple	Need of costly current sensors, sensitive to disturbances
IV		Coup de fouet [39]	Easy	Not accurate
V		Battery cranking voltage [40]	Much easier & efficient	Poor accuracy
VI		Adaptive control system [41]	Online	Sensitive to modeling Accuracy
VII		Fuzzy logic [42-44]	Simple and accurate	Slow convergence
VIII		Statistical Model/Regression technique [45]	Online Accurate	Sensitive to slops of battery parameters

The SoH estimation methods mainly include durability model-based open-loop methods and battery model-based closed-loop methods [46]. In durability methods, the changes in capacity fade and internal resistance are directly predicted. The durability models describe the increase in the value of resistance and battery terminal voltage. Based on durability characteristics, a storage life model is obtained for SoH estimation.

The battery model-based closed-loop methods use least-squares methods, Kalman filtering and other adaptive algorithms (such as fuzzy logic), to identify the battery capacity and internal resistance according to the operating data.

Note: We have selected the statistical model/Regression formula for SoH estimation in BMS chip implementation. In our proposed FPGA based BMS chip implementation (section-4), regression formula is computed using Statistical Controller for SoH estimation.

Statistical Model

The cause of battery health deterioration is the effect of aging on the grid, electrodes, contacts, corrosion and charging /discharging cycles. The SoH of a lead acid battery is modeled using multivariate linear regression [47] on the aging effect and in-time consumption of the battery. It has seen that the slopes of parameters like specific gravity, terminal voltage and internal resistance with respect to time (m , m' , m'' respectively) indicate the effect of age. Author has calculated the various slops from the collected data set by testing 12V-70Ah lead-acid battery [45].

In the statistical model, a formula is obtained after applying the multiple regression technique:

$$\text{SoH} = 1.0043 + 0.0088(\text{TT} \times \text{C}) + 3.8925 \text{ m}(\text{SG}) + 0.2444\text{m}'(\text{OCV}) - 0.0863\text{m}''(\text{IR})$$

Where TT is the run-time of the battery, C is the discharge rate and IR is the internal resistance. TT × C gives the ampere-hour consumption of the battery and m(SG), m' (OCV), m''(IR) are slopes refer to aging of the battery.

The computed results of statistical model showed that the SoH of lead acid battery is affected 60% by current consumption (for real cranking of a car for 15 sec), 30% by the IR slope and 10% by the remaining two parameters that are SG slope and the terminal voltage slope.

III. COMMERCIAL BMS ICs

Most of the available BMS are designed as embedded systems. Mostly they use specific software platforms and system hardware; those are not standard as yet. Three kinds of topologies have been implemented in BMSs, including centralized, distributed and modular structures [48]. BMS has become increasingly important in EVs & HEVs for safety of the system and user. Both the generic ICs and specialized BMS front-end ASICs are commercially available in market today. The generic BMS ICs require more design efforts than specialized BMS ICs, while ASICs perform excellently (measurement accuracy, flexibility) in BMS operation than generic ICs. The comparison of different commercial BMS products developed by leading battery management IC manufacturers is presented in the table 6.

Table 6. Comparison between different commercial BMS ICs

BMS Features	Texas Instruments BQ78PL114 [49]	Linear Technology LTC6802 [50]	Maxim DS2726 [51]	Intersil ISL9217 [52]	O2Micro OZ890 [53]	Analog Devices AD7280A [54]	AMS AS8506C [55]	Atmel ATA6870 [56]	FreeScale MC33772 [57]
Measured Cell Parameters	Voltage, current, temperature, impedance	Voltage, current, temperature	Voltage, current	Voltage, current, temperature	Voltage, current	Voltage, current, temperature	Voltage, temperature	Voltage, current, temperature	Voltage, current, temperature, impedance
Measured Pack Parameters	N/A	Voltage, Temperature	N/A	Voltage, temperature	temperature	Voltage, temperature	Flexible for voltage	Voltage, temperature	voltage
Cell Balancing	Inductive shuttle charge	Shared pins external resistor	Charge shunting	External balancing resistors	External equalized resistance	External balancing transistors	external DC-DC Flyback converter	external N-channel MOSFETs	embedded balancing transistors
Safety Protection	<ul style="list-style-type: none"> fail-safe operation of pack protection circuits three power FETs one secondary safety output fuse 	<ul style="list-style-type: none"> over/under voltage, over/under temperature 	<ul style="list-style-type: none"> over/under voltage over current short circuit current 	<ul style="list-style-type: none"> over/under voltage, over current, short circuit current over/under temperature 	<ul style="list-style-type: none"> over/under voltage, over current, short circuit current over/under temperature 	<ul style="list-style-type: none"> over/under voltage, over current, internal short protection 	<ul style="list-style-type: none"> over/under voltage 	<ul style="list-style-type: none"> over/under voltage, over current over heating 	<ul style="list-style-type: none"> over/under voltage, over current
SoC/SoH Estimation	SoC	none	none	none	SoC	None	Safe Operating Area (SOA)	SoC	SoC
Data Logging	On PC based GUI only	no	no	no	EEPROM	Data memory		no	EEPROM
Communication	PowerLAN, SMBus	SPI protocol	unknown	I ² C host interface	I ² C	SPI protocol	SPI protocol	SPI protocol	SPI protocol

Most of the commercialized ICs for BMS operation include one or more circuits like multiplexer, A/D converter, temperature sensors, logic to derive balancing loads and digital signal processors (DSPs). Some of them also include intelligence algorithms for battery state monitoring. Few commercialized ICs are actually not true ASICs, but are microcontroller or FPGAs that are preprogrammed or preconfigured for BMS operation. The example of configurable device is ACTEL's A40MX02-PL537: an FPGA customized for BMS operation.

Among all the presented commercialized BMS manufacturers in table 6, the Texas Instruments and Linear Technology products are preferred by the peoples. ICs (from Texas Instruments (TI), Atmel, Intersil) for small battery packs may seem attractive, but trying to shoehorn them in large battery packs, is an exercise in futility.

The TI products in particular provide good BMS solutions. The latest TI design guide shows a system example for an active balancing BMS. In this BMS example, the TMS570LS0432 device is a high performance, automotive grade microcontroller with extensive diagnostics capabilities that analyses the data from all cells and generates active cell balancing commands. Self-diagnostic functions are enabled to monitor the status of TMS570LS0432 during run time. The TMS570LS0432 microcontroller commands EMB1402 EVM through the SPI port to monitor the battery cells and perform charge/discharge from one battery cell to an external 12V supply. The EM1402 EVM is designed as the battery monitor and cell balancing engine. The cell-monitoring architecture is based on the BQ76PL455A-Q1 IC. The BQ76PL455A-Q1 monitors and detects several fault conditions, including – Under voltage, Over temperature, Communication faults. The TMS570LS0432 MCU configures and commands the BQ76PL455A-Q1 IC to measure the voltages of all cells and read the error status through the UART port. The user can view the cell status and control cell balancing from a GUI running on the host PC. Linear Technology's products are great in large battery packs because they include stackable architecture that suits well for >1000V systems, 1MHz serial interface daisy chains to adjacent devices, built-in self tests, high noise immunity and 48-lead exposed pad QFN & LQFP packages. But, these approaches were poorly implemented as they demand better understanding of the real world challenges of large batteries.

Most of BMS ICs available in market are capable to estimate the SoC of the battery. However, a few BMS can also estimate both SoC and SoH of the battery. For example, ZMDI- the analog mixed signal company developed Intelligent Battery Sensor IC ZSSC1856. The ZSSC1856 is a dual-channel ADC with an embedded microcontroller for battery sensing/management in automotive, industrial, and medical systems. One of the two input channels measures the battery current IBAT via the voltage drop at the external shunt resistor. The second channel measures the battery voltage VBAT and the temperature. An integrated flash memory is provided for customer-specific software; e.g., dedicated algorithms for calculating the battery state. ZSSC1856 estimates integrated, precision measurement solution for accurate prediction of battery state of health (SoH), state of charge (SoC) [58].

IV. PROPOSED FPGA BASED BMS CHIP IMPLEMENTATION

Please note, as a case study for FPGA based BMS chip implementation, we have used our previous work models: Neuro-Fuzzy & Statistical model (discussed in section 2) for SoC & SoH indication respectively [4]. The presented research work is primarily focused on a Lead-Acid Battery which is used for cranking of the engine and slow electric discharge in non-electric automotive. Most of the existing BMS systems use master controller that includes SoC & SoH algorithms and these estimation algorithms are mainly the parts of the software. Due to limitation of BMS hardware design, the accurate algorithms which require higher computational power could not be used in these master controllers. The proposed approach is an attempt to design a dedicated FPGA device for Advanced BMS which can house accurate SoC and SoH algorithms. No other researcher has developed it for Lead-Acid until now. The work is important because it creates an option for a BMS system to have a separate high computational power chip to execute accurate BMS algorithms with low capacity master controller.

The FPGA based BMS chip implementation uses MATLAB to FPGA design flow as shown in figure 3. Figure 3 is also an outline for the hardware implementation of SoC & SoH models. For ease of FPGA implementation, SoC & SoH models are designed in Matlab/Simulink [59]. Later, Simulink model is converted into HDL codes (RTL model). RTL (register transfer level) model details the design abstraction to the Advanced BMS model in terms of the flow of digital signals (data) between the hardware registers, and the operations performed on those signals. The SoC and SoH estimated from Simulink model and RTL model are compared in the submitted manuscript. The well designed RTL model of SoC/SoH observer proves its suitability for FPGA implementation. In addition, design validation is performed using functional or behavioral simulation [60]. Further, we have performed logic synthesis to achieve a netlist of gates/blocks, specified in FPGA devices and also performed mapping to get target FPGA architecture. Placement is followed by mapping to select the optimal position for each block.

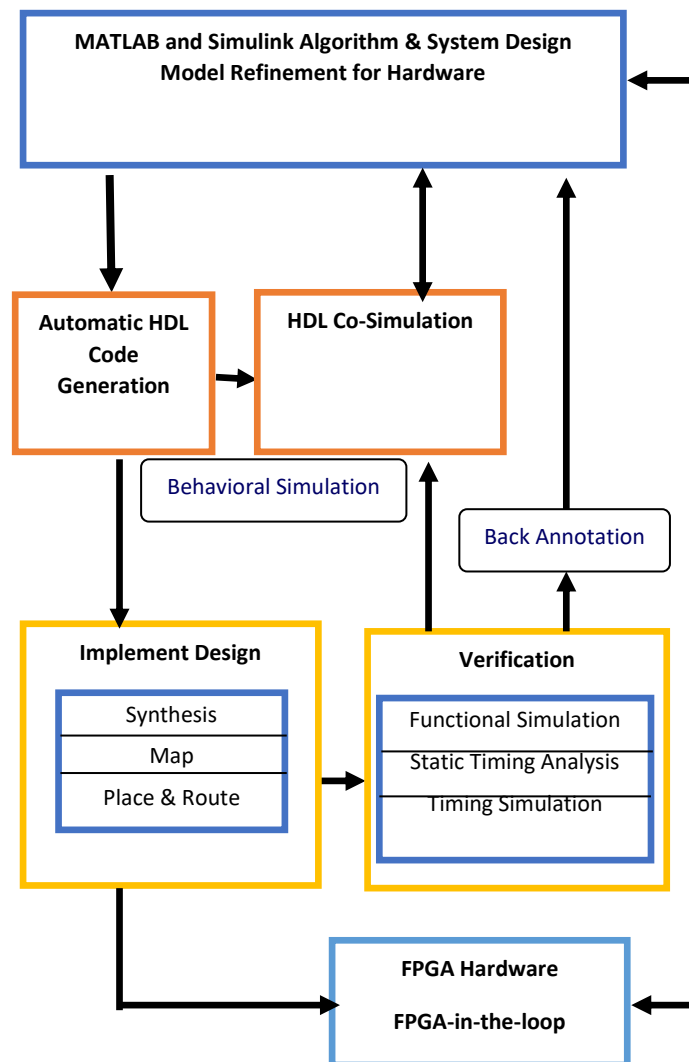


Figure3: FPGA Design Methodology using MATLAB

The basic goals of placement in FPGA design flow is to locate functional blocks and interconnects those are required to route the signals between blocks. A good placement is extremely important for FPGA system to reduce the design cost and power loss. Placement directly affects the routability and the performance of FPGA design. Routing is the last step in the design methodology prior to generating the bit file required to program the FPGA. Lastly, timing simulation is performed to validate the logical correctness of the design considering the time response of the FPGA device.

In the FPGA design methodology, it takes the mapped, placed and routed design as input and generates the necessary bit stream to program the logic and interconnects to implement the intended logic design and layout on the target FPGA device.

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The block diagram of proposed FPGA based BMS chip implementation is shown in figure 4. Here the lead-acid battery is first connected to the interfacing circuitry. The interfacing circuit is used to extract the five parameters-1) V-Terminal Voltage 2) I-Current 3) R-Internal Resistance 4) T-Temperature 5) Tc-Consumption Time. For data collection, we have used laboratory based circuits- Bitrode battery test system and Agilent impedance measurement system at R&D Exide Industries Ltd, Kolkata, India. The data set was collected for a 12V, lead acid battery MF40sv [61] used in Maruti Suzuki Alto car.

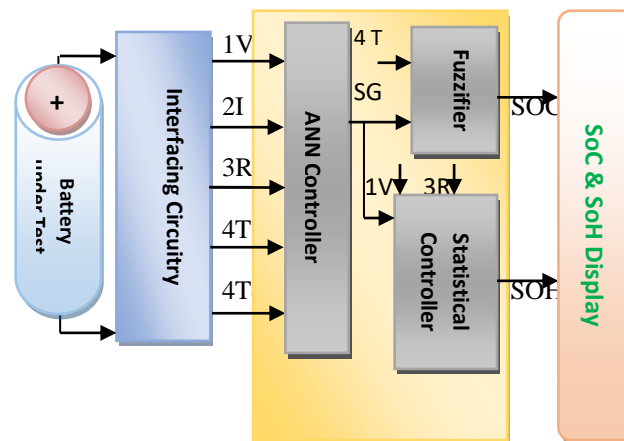


Figure4: Block Diagram of FPGA Implementation for SoC & SoH Indication

These test set parameters remain in the FPGA (memory block) and will be used by FPGA processing blocks. The SoC & SoH models are implemented in FPGA blocks. Three basic FPGA blocks are implemented within the battery model: a) Artificial Neural Network controller b) Fuzzy Logic controller c) Statistical Controller. ANN controller computes the neural network algorithm to measure SG of battery electrolyte. The SG and battery temperature are then applied to fuzzy logic controller to estimate the SoC of the battery. The combination of ANN controller and Fuzzifier is termed as Neuro-Fuzzy Controller that estimates SoC of a battery. The statistical controller block computes the regression formula to estimate the SoH of the battery. The display of SoC & SoH maintains the past status till input discharge current and time parameters are zero. As soon as discharge current and discharge time appears at input, the algorithm starts executing a new set of parameters to compute new values on display. Clock triggering regulates the process of FPGA based BMS chip implementation.

The proposed FPGA design scheme of BMS chip implementation in present research will be preferred to suit well in EVs & HEVs because of small size and combined estimation of accurate SoC & SoH of the lead-acid battery.

V SIMULATION RESULTS

The simulation results of ANN training, Simulink model and RTL model are drawn and tested on the experimental data collected for Exide make MF40sv 12V lead-acid battery, used for non-electric automotive. In this automobile, the battery supports engine cranking to start the vehicle and slow discharge to support electric load. In our work, the model has been developed for two discharge currents as per the application requirement.

- (a) Slow discharge of 12A constant current which is a lab simulation of the DC electric load after a real time measurement with the DC load in the car.
- (b) Engine cranking current of 150A for 5sec followed by a rest of 15sec simulates the engine cranking current.

A set of experiments were conducted at different environmental temperatures (0°C, 27°C, 40°C), for various state of charge of the battery (100%, 75% and 50%) and for various ages of the battery (Fresh, One Year Old and Two Years Old).

ANN simulation is a method for the network training, verification and testing to check if it meets the expectations. ANN simulation is expected here to predict the ANN output (SG of electrolyte) very closer to the target value of SG. The target values are desired values of SG for a given set of five inputs. The neural network utilizes feedforward topology for its ANN architecture and back-propagation learning algorithm for its training. The numbers of neurons in input, two hidden and output layers are 5, 11 in each, and 1 respectively. The

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ICTM Value: 3.00

activation function for both hidden layers is logsigmoid and for output layer is purelin. The basic study of the neural network is done on two the training functions, trainbr and traingdm. The neural network algorithm uses the supervised learning for network training. The learning rules adjusted the weights and biases of the network in order to move the network output closer to target output. Please note that in the present work, we have used weights and biases from previous work [61]. Once the network is trained within the acceptable error, the network simulation is done. Figure 5 depicts the performance plot, the value of the performance function versus the iteration number. The number for iterations required for the training depend on selection of weights, biases, network, data set and covering algorithms. The mean square error (MSE) is chosen here as the performance function for the neural network. The MSE is defined as the average squared difference between the ANN output and the target. The MSE value measured in performance plot is very small i.e. $1.2043e-06$ obtained in 7 epochs that ensures, the ANN is well trained. It is also observed that the training and test curves have approximately similar characteristics, indicating minimum overfitting occurs in the performance plot.

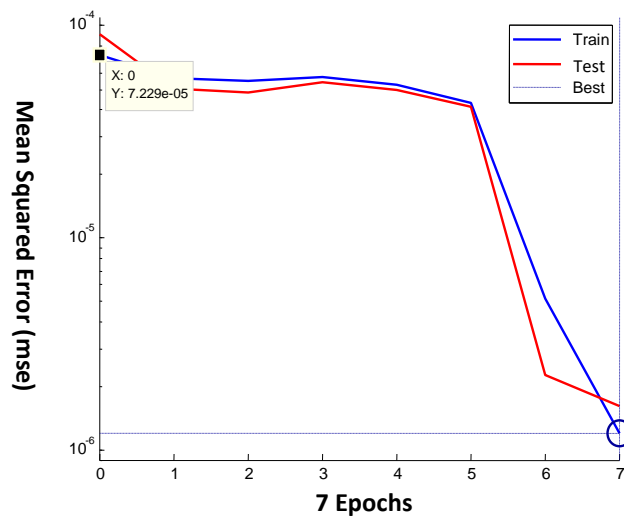


Figure5: Mean square errors versus iteration

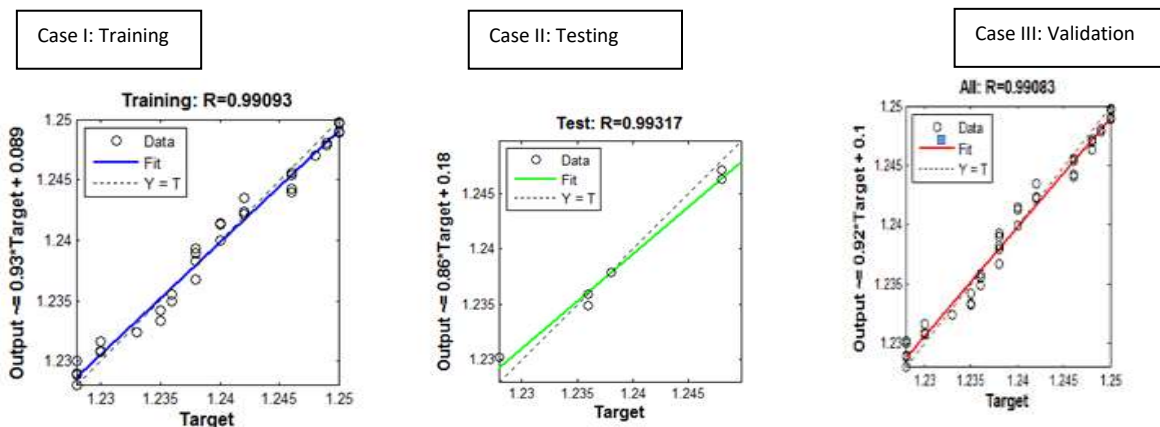


Figure6: Regression plots for training, testing and validation data

A linear regression is also performed between the network outputs & the corresponding targets to validate ANN. The ANN response analysis in figure 6 depicts that the output tracks the targets very well for training, testing, and validation. The regression, the correlation coefficient (R-value) between the outputs and targets, is a measure of how well the variation in the observed output is explained by the targets. The R-value is observed 0.9908 for the total response. The R-value is very close to 1, which indicates a good fit (perfect correlation between targets and outputs). The solid line in each plot represents the correlation through regression R-value between outputs and targets during the training and simulation [62]. It is very clear in figure 6 that the outputs

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align well with targets for training, validation and testing data which means the model is much more accurate. The achieved ANN training accuracy is more than 99%. The variations in the estimated SoC of advanced BMS with the increase in SG & temperatures compensated at 0°C, 27°C & 40°C are shown in Fig. 7. The simulation results are performed for one year old lead-acid battery operating in real cranking mode of car operation.

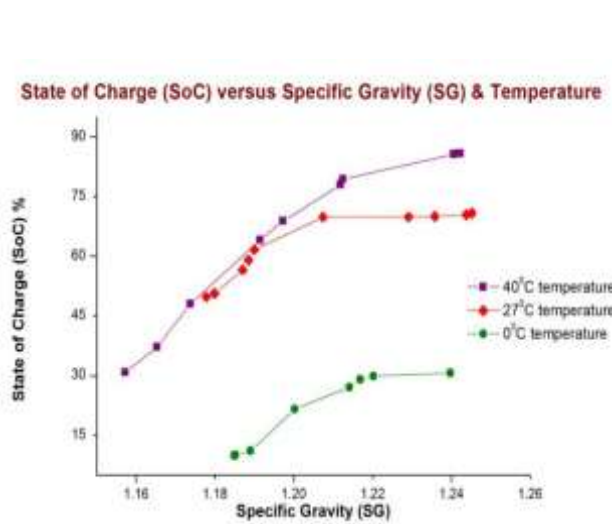


Figure7: SoC versus SG & Temperature

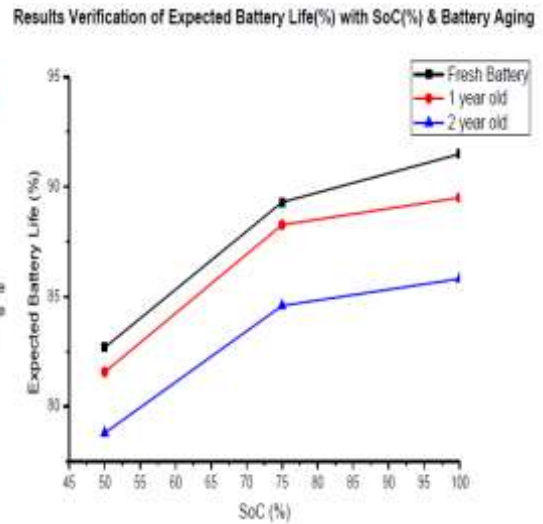


Figure8: Expected Battery Life (%) versus SoC (%)

It is observed that SoC is high at higher SG and also increases with increase in temperature. 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, figure 7 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 percentage of expected battery life for various ages corresponding to varying SoC has been shown in figure 8 to support to the real cranking load at 27°C. The expected battery life is decreasing with the age of the battery and with decrease in state of charge.

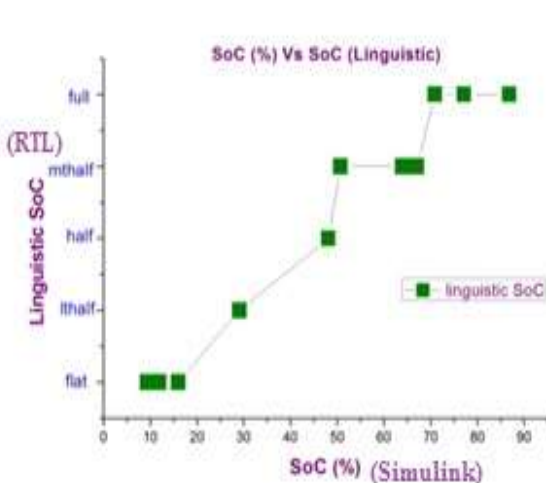


Figure9: SoC (%) versus SoC (linguistic) models

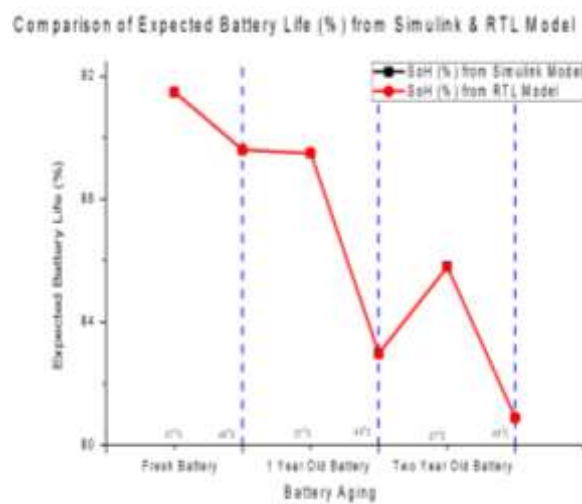


Figure10: Expected battery life predicted from Simulink Vs RTL models

The Simulink model and RTL model of proposed Advanced BMS design are discussed in our recent work [59] and [60] respectively. The simulation results of both models for SoC and expected battery life are elaborated in

figure 9 and 10 respectively. In figures 9 & 10, the well alignment of SoC predicted from the Simulink model & RTL model and of the expected battery life predicted from the Simulink model & RTL model indicates the consistent model accuracy throughout the design flow. Thus, the RTL model of Advanced BMS is well designed and can be easily implemented on the targeted FPGA after synthesis and bit file generation.

The simulation performed in this research work is based on the constant discharge of 12A and 150A of lead-acid battery for non-electric automotive. The developed algorithms and Advanced BMS can be easily configured for EVs and HEVs where load profile is more dynamic. The behaviour of lead-acid battery model with pulsed charging/discharging load especially demanded in EVs and HEVs is also presented in figures 11.

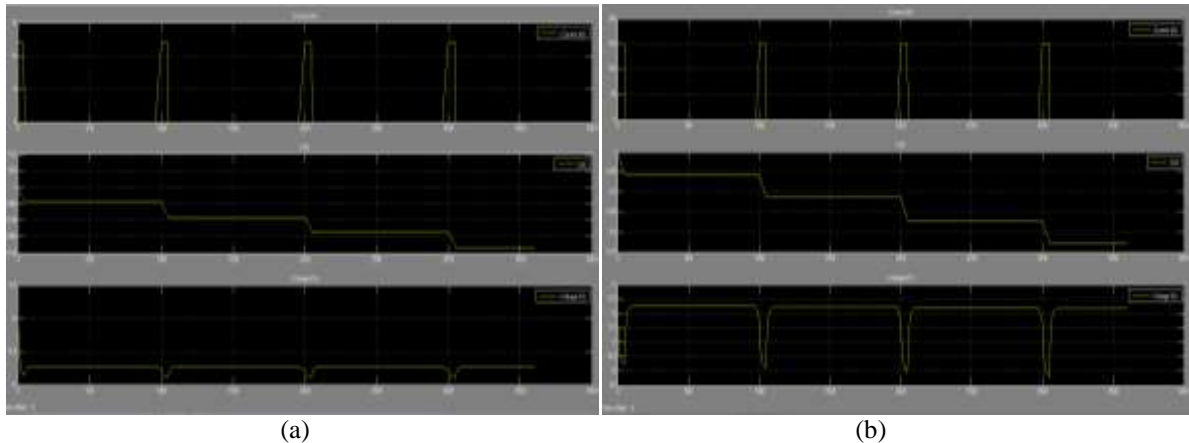


Figure11: Lead-acid Battery Model Test Results (a) with 12A (Slow Discharge) and (b) 150A (Real Cranking) pulsed charging/discharging load respectively

It is seen here that SoC of lead-acid battery is decreased in the pulse width of 12A and 150A discharge respectively and remains constant when discharge current is zero.

VI. CONCLUSIONS

In this paper, we have presented SoC & SoH algorithms and FPGA implementation of BMS controller. A comparison of existing commercial BMS and their imperfection are outlined. Most of the existing BMS estimate SoC using coulomb counting and OCV. A Few of them also combine Kalman Filter with SoC algorithm. However, each of them depends on the direct measurable electrical parameters and ignores effect of electrochemical reactions. Further, most of the existing BMS either do not provide SoH at all or provide it as a function of capacity degradation over the battery usage. Capacity degradation alone cannot provide accurate battery health because battery health is a complex function of multi parameters. Battery health depends on electrolyte, electrode, separators and SEI (Solid Electrolyte Interface) layer which unfortunately do not often reflect in graceful capacity degradation but a sudden capacity loss. In most cases, after certain age of the battery, chances are huge that capacity degrades suddenly due to SEI layer damage or electrodes damage. To predict the aging it is essential to reach out to get a model that includes electrochemical parameters or one that can map the electrochemical behavior of the battery. Our paper focuses the electrochemical behavior modeling of a battery and its FPGA implementation to provide accurate SoC and SoH. The selected Neuro-Fuzzy approach and statistical model have the capabilities to adopt nonlinear electrochemical behavior of battery and map them to accurate SoC & SoH respectively. The model also has high degree of confidence for control strategy & implementation of a BMS. The selected battery model is validated by simulation and experimental studies for a lead-acid battery. The selected model is very compatible to develop FPGA based BMS. In the adopted design methodology i.e. MATLAB-to-FPGA design flow, SoC & SoH algorithms can be easily trained, simulated, validated in MATLAB and translated into the FPGA architecture using the different EDA tools integrated together. Thus, our proposed approach of FPGA based BMS chip implementation to determine SoC & SoH is computationally effective for simulation, design and real-time management of battery-powered systems. Off-course, FPGA based BMS should be preferred over other existing BMS because of low Non-recurring engineering (NRE) cost, low power consumption, high speed of operation, large reconfigurable logic, large data storage capacity and hence better performance.

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