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Original Article

Real-Time Monitoring System for Lead Acid Battery Health and Performance using Fuzzy Logic and HIL Simulator

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Abstract - *The performance and health of lead-acid batteries used in various applications such as automotive, industrial, and renewable energy systems significantly impact their operational efficiency and longevity. Monitoring the performance of battery health in real time prevents failures and extends battery life. This paper proposes a lead-acid battery real-time monitoring system health and performance using a fuzzy logic controller and a Hardware-in-the-Loop (HIL) simulator. The proposed system measures critical battery parameters such as voltage, current, and temperature. It processes this data with fuzzy logic algorithms to calculate the battery's State of Charge (SOC) and State of Health (SOH). The HIL simulator provides a virtual platform for testing and validating the system in real time. The findings suggest that the proposed method can produce reliable estimates of battery SOH, making it a promising solution for real-time battery monitoring in various applications.*

Keywords - *Fuzzy Logic Controller, HIL Real-time simulation, Lead-Acid Battery, State of Charge, State of Health.*

1. Introduction

Lead-acid batteries have been widely used for over a century in various applications, including automotive, backup power, and renewable energy storage systems [1]. However, as these batteries age, their performance and health gradually deteriorate, resulting in reduced capacity, shortened lifespan, and potential failure [2, 3]. To address these issues, researchers have developed several techniques for monitoring battery health and performance [4]. In recent years, real-time simulation has emerged as a powerful tool for battery monitoring and evaluation [5, 6]. Real-time simulators provide a virtual environment for testing and evaluating battery behavior under different conditions, enabling operators to identify potential issues and take corrective actions in a timely manner [7]. Real-time monitoring of battery health and performance is crucial to prevent failures and extend battery life [8].

Despite the advancements in battery monitoring techniques, there still exist research gaps and challenges in effectively monitoring the health and performance of lead-acid batteries. One major challenge is accurately estimating the state of health (SOH) of the battery, considering uncertainties in battery parameters such as temperature, aging, and load variations [9, 10]. Traditional monitoring approaches often struggle to handle these uncertainties, leading to inaccurate estimations and ineffective maintenance strategies. Additionally, there is a need for a real-time monitoring system that integrates monitoring techniques with advanced control strategies to provide valuable insights for operators and decision-makers [11 -13].

To address these research gaps, this paper proposes a novel real-time monitoring system for lead-acid batteries, utilizing fuzzy logic and a Hardware-in-the-Loop (HIL) simulator [14, 15]. By integrating a fuzzy logic controller (FLC), the system can effectively handle uncertainties in battery parameters, resulting in high-accuracy estimations of the battery's state of health [16]. The research aims to enhance the performance and longevity of lead-acid batteries, which are widely used in various critical applications [17]. The proposed monitoring system not only detects early signs of battery degradation using fuzzy logic algorithms but also provides valuable information for maintenance and replacement decisions [18, 19].

To develop the monitoring system, the research team employs various experimental techniques, such as electrochemical impedance spectroscopy and cyclic voltammetry, to characterize the battery's behavior under different conditions [20, 21]. The data collected from these experiments are used to develop an accurate model of the battery's behavior, which is then integrated into the HIL simulator [22]. This approach enables real-time monitoring of essential battery performance and health indicators, including state of charge (SOC), state of health (SOH), and internal resistance [23]. Moreover, the system incorporates a data visualization tool that presents the battery's performance parameters in real time, facilitating operators in promptly identifying potential issues and taking appropriate corrective actions [24,25,26].

In summary, this research addresses the research gap in real-time monitoring of lead-acid batteries' health and performance. By leveraging fuzzy logic and HIL simulation, the proposed monitoring system aims to accurately estimate the battery's state of health and provide real-time insights for effective maintenance and replacement strategies. The integration of advanced control strategies and data visualization tools enhances the capabilities of the monitoring system, contributing to improved battery performance, extended lifespan, and enhanced reliability in critical applications.

The rest of the paper is organized as follows: Section 2 describes the battery modelling, while Section 3 presents the data collection and estimation techniques; Section 4 interprets the research findings and their implications; Section 5 presents the monitoring data and simulation results; and then the conclusion summarises the research work and its contribution.

2. Battery Modelling and Real-Time Simulation

2.1. Battery Model

There are several types of models available for lead-acid batteries, including empirical, electrochemical, and circuit models.

The electric circuit model is the best type of model for lead-acid batteries because it provides a good balance between accuracy and simplicity. The lead acid battery electric circuit concept is shown in Fig. 1. Considering that it is based on a straightforward equivalent circuit that is simple to incorporate in circuit simulators or control algorithms, it can provide accurate predictions of the battery's voltage and current behaviour under a variety of loads and situations. In the design and optimization of lead-acid battery systems for backup power, electric vehicles, and other applications, the battery circuit models are frequently used.

The equivalent circuit model for a lead-acid battery can be expressed mathematically as follows:

$$V_{bt} = V_{OC} - \mathrm{I}R_i - V_{pr} - \mathrm{I} * (R_e // C_e) \quad (1)$$

Where V_{bt} is the battery terminal voltage, V_{OC} stands for the battery's open circuit voltage. The battery's current is represented by the symbol I, R_i is the battery's internal resistance., V_{pr} is the voltage drop across the concentration polarization layer, R_e is the resistance of the battery's diffusion polarization layer, and C_e is the capacitance of the battery's diffusion polarization layer.

2.2. Real-Time Simulation

The Simulink simulation model is initially created and then modified in accordance with the subsystem separating rules and the RT-LAB model libraries. The RT-LAB system uses the original Simulink model to create parallel tasks, which are then executed on each CPU of the multi-CPU machine. Data is transferred between jobs using shared memory, which has very low latency. Additionally, the RT-LAB system offers a unique feature called multi-step length computing, which enables calculating various modules of a complex model at different time steps. This feature enhances the precision and convenience of simulating a vehicle.

The process of creating the model using RT-LAB software involves several steps. First, the model is divided into simulation nodes based on different subsystems. Then, MATLAB Real-Time Workshop generates code compiled in the real-time simulator. Once the model is compiled, it can be loaded and executed in real time. The model's battery part comprises approximately 100 series-connected battery cells, while the auxiliary part includes components such as the VCU, charger, motor, and cooling fan. These subsystems interact with each other and with the BMS. To ensure real-time calculations, the model is divided into two nodes.

The model-building process of RT-LAB software involves several steps. Firstly, the model is divided into simulation nodes based on different subsystems. Next, code is generated using MATLAB Real-Time model and compiled in the real-time simulator. The compiled model can then be loaded and executed in real time. The battery part of the model comprises around 100 series-connected battery cells, while the auxiliary part consists of the VCU, charger, motor, cooling fan, etc. These different subsystems interact with one another and with the BMS. To facilitate real-time calculation, the model is split into two nodes.

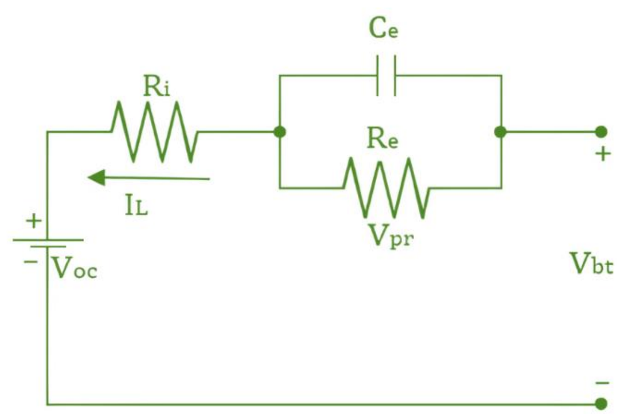

Fig. 1 A battery electric circuit model of a lead-acid battery

3. State of Health (SOH) Estimation

The actual SOH values are obtained with the help of the capacity fading method. This method involves measuring the battery's capacity (in Ah) at different states of charge (SOCs) and comparing the results to the battery's rated capacity. The capacity fading method can be implemented by performing a series of discharge tests at different discharge rates and measuring the battery's capacity at each discharge rate. The capacity fading method is based on the idea that the capacity of a lead-acid battery will decrease as the battery ages and its SOH declines. For example, if the rated capacity of a lead-acid battery is 100 Ah, and the capacity measured at a particular discharge rate is 95 Ah, the SOH of the battery can be estimated to be 95%. If the capacity measured at a different discharge rate is 90 Ah, the SOH can be estimated to be 90%. By comparing the measured capacities at different discharge rates to the battery's rated capacity, it is feasible to calculate the battery's SOH. Eq. 2 gives the measured value of Actual SOH.

$$\text{Actual SOH} = \frac{\text{Total Capacity (Ah)}}{\text{Beginning of life (BOL) Capacity (Ah)}} \qquad (2)$$

The life parameters of batteries were examined using the usual cycle counting approach based on the outcomes of the results. According to the results of the experiment, the number of cycles has an impact on the battery's life, the investigation is done on the battery's performance after prolonged use and the correlations between changes in battery discharge efficiency, energy efficiency, discharge capacity, internal resistance, and other factors are examined. Table 1 displays the results of the cycle counting method and the actual procedures. The true SOH is estimated using raw data from multiple measures. These Actual SOH values will be used to compare the results of the subsequent chapters.

3.1. Estimation of SOH using Fuzzy Logic Controller

During an experiment employing an FLC to estimate the SOH of a lead-acid battery, various parameters are typically measured and recorded. The parameters that are commonly measured are voltage, current, temperature, time, and SOH. In particular, the input variables to the fuzzy logic controller are voltage, current, temperature, and time, while the output variable from the controller is the estimated SOH.

These parameters are crucial in providing insights into the battery's overall health and performance, which can be used to make informed decisions regarding the maintenance and replacement of the battery. Table 2 displays the fuzzy sets for the input and output variables.

Each input and output variable in this table has a domain or range of possible values that it can take. A membership function for each variable determines the degrees of membership for each value inside its domain. The degree of membership for each value in the domain is denoted by the terms "high," "medium," and "low" in the membership function.

For example, a voltage value of 13V would have a high degree of membership in the voltage input variable, while a voltage value of 8V would have a low degree of membership. Similarly, a SOH value of 95% would have a high degree of membership in the SOH output variable, while a SOH value of 30% would have a low degree of membership.

Fig 2 shows Implement the fuzzy logic controller using a programming language, such as MATLAB/Simulink. The controller takes the input variables (voltage, current, temperature, and time) and calculates the output variable (SOH) based on the fuzzy rules and membership functions.

Table 1. Comparison of conventional SOH and actual SOH

No. of Cycles	Cycle Counting Method	Actual SOH (Offline Measurement)
0	100	100
100	65	70
150	50	55.59
200	30	40.21
250	12.5	30.45
300	0	17.32

Table 2. Fuzzy sets

Input/Output Variable	Domain	Membership Function
Voltage	0-12 V	High: 12-14V
		Medium: 10-16V
		Low: Outside range
Current	0-12 A	High: 4-6A
		Medium: 2-8A
		Low: Outside range
Temperature	0-42°C	High: 25-30°C
		Medium: 20-35°C
		Low: Outside range
Time	0-4.2 h	High: 3-5h
		Medium: 2-6h
		Low: Outside range
SOH	0-100%	High: 80-100%
		Medium: 50-90%
		Low: 0-80%

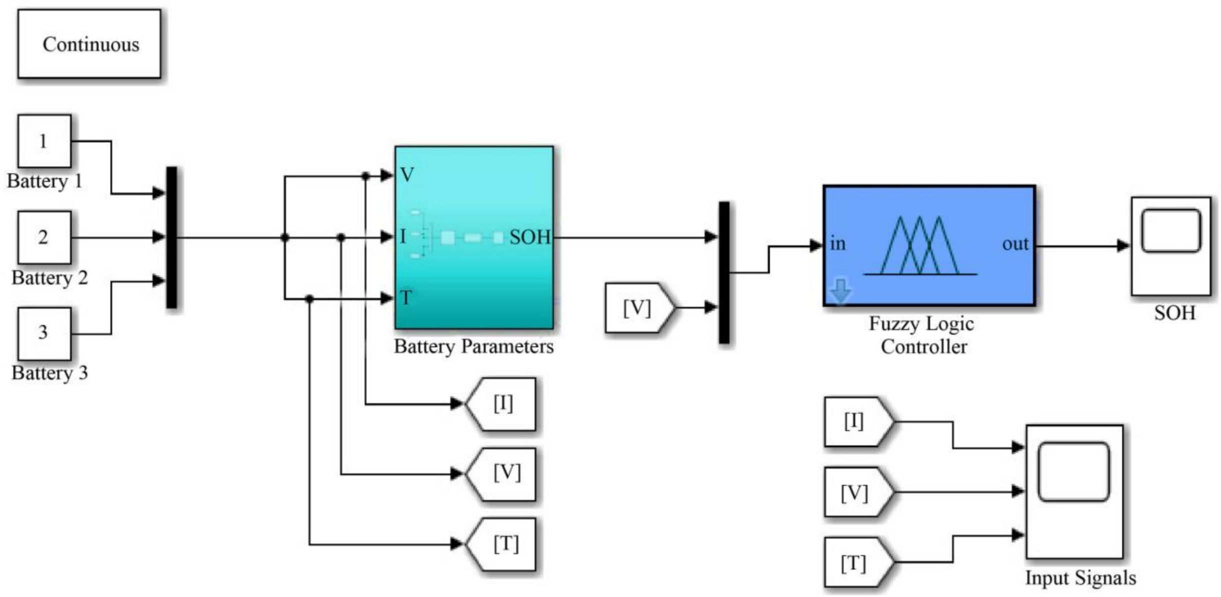

Fig. 2 Simulink model of fuzzy logic controller for estimating SOH

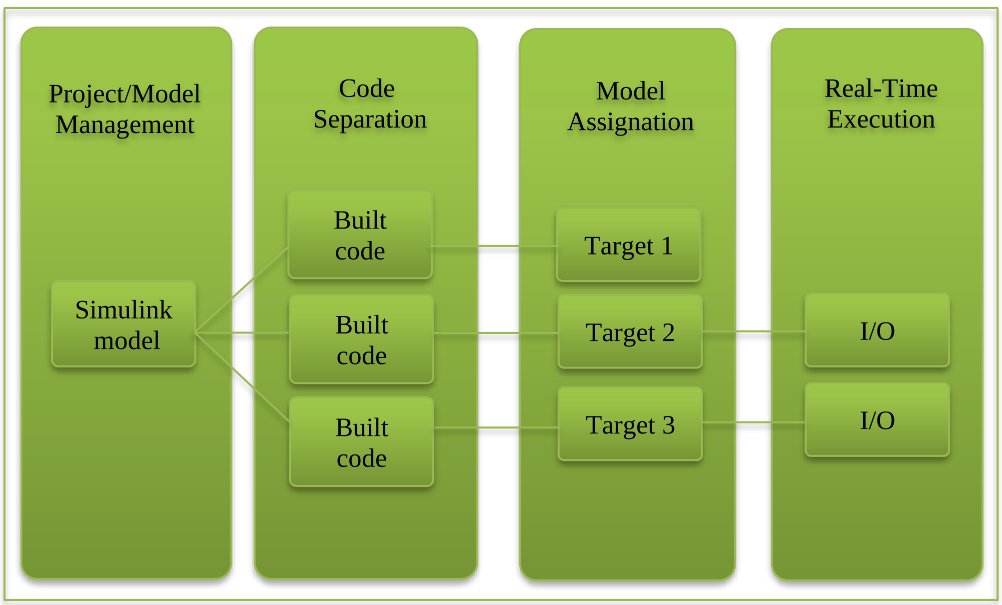

Fig. 3 General architecture

3.2. Implementing HIL-Based RT Lab System Architecture

Firstly, the fuzzy logic controller emulates the lead-acid batteries' behaviour through integration with the HIL real-time simulator. The simulator creates a virtual environment to test and evaluate the battery's behavior in real time. Then, the fuzzy logic controller is tested using different input variables, and if necessary, the controller is refined. The controller must precisely predict the lead-acid batteries' SOH under varied circumstances.

The OPAL-RT Real-Time Digital Simulator (RTDS) model OP4510, which consists of a real-time Personal Computer (PC), a Central Processing Unit (CPU), and an FPGA, is the HIL device used in this work.

The general architecture of RT-LAB is presented in Fig 3, which utilizes a host-target model. During the design phase, the host is utilized to develop the model, and at runtime, it functions as a user interface that communicates with the target through Ethernet. The target PC is responsible for performing real-time computations and has a standard PC architecture, with one or two processors specifically allocated for Simulink model simulation.

These processors are connected to the rest of the system and I/O via an FPGA board using a PCI or PCI-Express bus. The number of I/O modules can be configured based on application requirements. By utilizing FireWire or PCI Express real-time communication links and switches, multiple targets can be interconnected to form a supercomputer with high computational power, making it ideal for real-time simulation of intricate systems.

4. SOH Estimation with HIL Real-Time Simulator

The steps taken to estimate the SOH using a HIL real-time simulator are as follows:

Set up the HIL real-time simulator to simulate the battery's behavior accurately. This may involve configuring the simulator to simulate different battery chemistries, cell types, and other parameters. Collected data from the battery under different conditions. This may involve performing experiments such as cycling the battery through different charge and discharge cycles, subjecting the battery to different temperatures, and other similar experiments. After the data collection, the next process is to extract the relevant information. This may involve using signal processing techniques to analyze the data and identify features indicative of the battery's state. Machine learning algorithms are used to analyze the data and estimate the battery's SOH. These algorithms can learn patterns from the data and use them to predict the battery's behavior under different conditions. Finally, the results have been validated for the SOH estimation. This can be done by comparing the predicted behavior of the battery with its actual behavior under different conditions.

SOH estimation with a HIL real-time simulator requires careful preparation, data collection, processing, and validation. By following these steps, we can obtain accurate estimates of the battery's SOH, which can be used to improve battery management and extend battery life. The HIL simulator can simulate the battery and its behavior in real-time while allowing the battery management system (BMS) to be connected and tested in a controlled environment.

This approach can provide a more accurate estimation of SOH compared to traditional methods, as it considers real-world conditions and usage patterns. Fig 4 shows the process involved in HIL Real-Time Simulator for BHPMS Design. The digital system-based process of designing various methodologies plays a major role in recent research works.

These methodologies generally include the process of data collection, validation, and system verification. In our research work, the HIL-based BHPMS design methodology is provided for accurate estimation of SOC and SOH of a rechargeable battery by using the HIL simulator.

5. Comparative Analysis

The model was tested in the RT-LAB environment, and the findings showed that the simulator was effective. The output obtained from the HIL real-time simulator gives the estimated SOH value using our advanced NN-based BHPMS. The estimated SOH is compared with actual SOH (Measured from the characteristics of Lead Acid Battery), SOH estimation with FUZZY Logic with and without cranking and the conventional cycle counting method.

The actual SOH is the benchmark value for the purpose of comparing it with the estimated SOH value. The results show that the FFNN-based BHPMS gives better results compared to the other methods. The HIL-based model was seen to estimate the expected/remaining battery life accurately, which is much similar to that of Actual SOH.

A comparison of the remaining State of Health (SOH) estimated using the Simulink model and the Hardware-in-the-Loop (HIL) model of the BHPMS is illustrated in Figure 4. Furthermore, Figure 4 shows that the expected or remaining battery life decreases as the battery ages for a 100% charged battery under varying constant temperatures of 28°C and 40°C. As the temperature rises, the anticipated battery life also decreases.

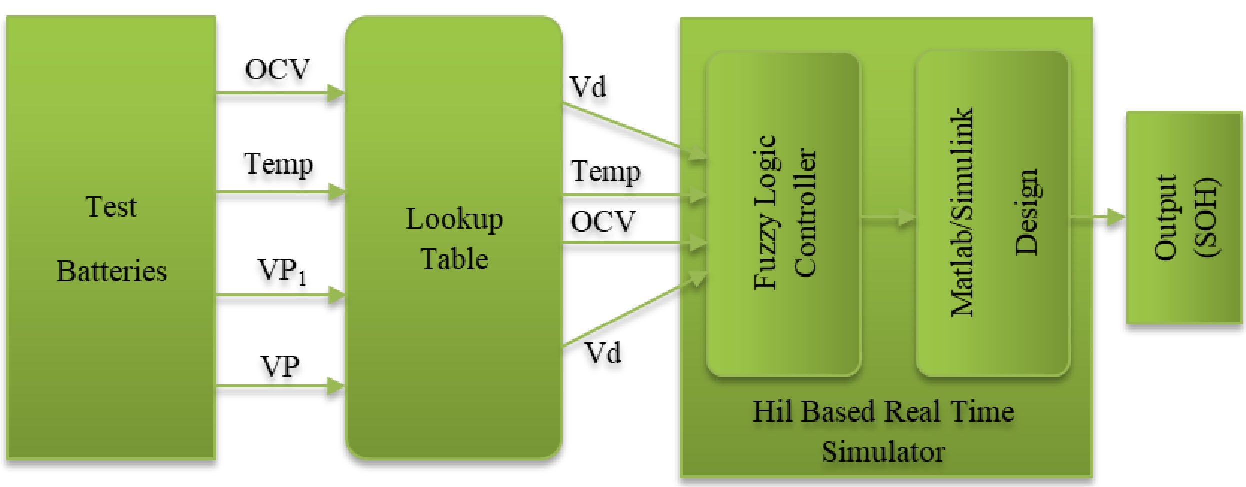

Fig. 4 HIL real-time simulator for BHPMS design

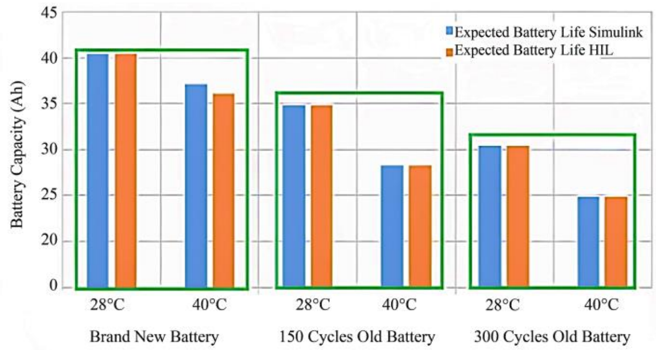

Fig. 5 Comparison of SOH estimation using simulink and HIL model

6. Conclusion

In the research carried out, the algorithms of SOH estimation were first developed using Neural Network & Fuzzy toolboxes in MATLAB, respectively. The algorithms of SOH estimations were then incorporated together in the Simulink model of BHPMS for the estimation of the SOH of the battery. The Simulink model of BHPMS was then transferred to the HIL-based RT LAB platform design methodology. The design methodology that was adopted includes a user-friendly interface that manages a unified environment along with other design tools, such as Xilinx ISE tools and other simulators and synthesizers for HDL that are widely used in the industry. The Simulink model also features the development of the BHPMS with no initial link to its implementation.

Furthermore, preference was given to the MATLAB-to-HIL design methodology to examine the product development cycle and decrease the design duration, which would offer a competitive advantage in terms of time-to-market. The Simulink flow also provides a cycle-accurate simulation capability for the system. Simulink model simulation results were also reviewed with the results of two different MATLAB tools, i.e., NN Toolbox and Fuzzy Toolbox and found that the Simulink model implementing the BHPMS was found to be a very efficient approach to indicate the SOH of battery. This is because; FFNN based Simulink model of BHPMS also has a high degree of confidence for control strategy & Advanced chip design. The Simulink model was simply used in the automatic generation of HDL codes, and then these HDL codes were used for BHPMS chip design. Thus, the Simulink model will be an easier and more convenient flow to develop HIL-based BHPMS, which reduces the product design time, and time-to-market and provides high performance.

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