

State of Health Classification for Lead-acid Battery: A Data-driven Approach

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Abstract. In general, methods that use a data-driven approach in estimating lead-acid batteries' State of Health (SoH) rely on measuring variables such as impedance, voltage, current, battery's life cycle, and temperature. However, these variables only provide limited information about internal changes in the battery and often require sensors for accurate measurements. This study explores ultrasonic wave propagation within a lead-acid battery cell element to gather data and proposes a data-driven approach for classifying the SoH. The results demonstrate that a neural network classifier can effectively distinguish between two classes: 1) batteries in a healthy state with SoH greater than 80%, and 2) batteries in an unhealthy state with SoH less than 80%. The data-driven approach introduced in this study, which uses ultrasonic wave data, provides valuable information relative to the changes in the internal cell of the battery. Conventional external measurements may not capture this information. Consequently, it eliminates the need for additional sensor installations and offers a promising alternative for SoH classification.

1 Introduction

For decades and extended periods, lead-acid batteries have occupied a preeminent position within the realm of energy storage systems [1]. This is due to its wide array of applications, from automotive vehicles to uninterruptable power supplies [2]. It is, therefore, crucial to ensure the reliability and longevity performance of lead-acid batteries to ensure that they will continue their purpose across various industries. In particular, a mechanism to assess the lead-acid battery's State of Health (SoH) is imperative as it directly impacts its operational efficiency and overall lifespan.

A widely adopted measure for assessing battery aging is the State of Health (SoH) [3-4]. SoH is determined by the battery's current and original capacity ratio. Generally, there are three main approaches to estimating SoH: direct measurement, model-based, and data-driven

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[5]. Among these approaches, data-driven methods have gained prominence due to the availability of data and advancements in machine learning [6-9]. These methods extract relevant features from large datasets to train models for SoH estimation. While these methods may need intricate procedures in terms of training, implementation of the trained models is generally uncomplicated. When the input features undergo careful processing and selection, data-driven approaches have the potential to attain exceptional accuracy.

Conventional data-driven approaches for SoH estimation have relied on measuring external variables such as impedance, voltage, current, battery life cycle and temperature. Gathering data given these variables often necessitates using additional sensors for precise measurement and the data typically provide limited information about the internal changes in the battery. This paper explores an innovative method of gathering nuanced information relative to internal battery changes by utilizing ultrasonic wave propagation within the lead-acid battery cell element. Moreover, a neural network classifier is developed to distinguish between two classes effectively: 1) batteries in a healthy state with SoH greater than 80% and 2) batteries in an unhealthy state with SoH less than 80%. This data-driven SoH classification approach offers the potential to provide a deeper understanding of the internal dynamics and condition of the lead-acid battery in a non-intrinsic way.

The remainder of the paper is structured as follows. Section 2 provides a detailed discussion of the materials and experimental setup used to derive the data-driven classifier. Section 3 presents the findings and analysis based on the results, followed by the conclusion in Section 4.

2 Materials and Methods

As shown in Fig.1, ultrasonic waves are used to traverse the cell element unit of a lead-acid battery using one ultrasound transmitter and three ultrasound receivers. The three ultrasound receivers are strategically placed in different locations within the cell element unit to investigate various ultrasonic response signals, namely transmissometry signals, diffracted signals and reflected signals. The measured signals from the transmitter and receivers are represented in the following equations below.

$$v_o(t) = V_0 \sin(\omega_{sig}t + \varphi_0) \quad (1)$$

$$v_1(t) = V_1 \sin(\omega_{sig}t + \varphi_1) \quad (2)$$

$$v_2(t) = V_2 \sin(\omega_{sig}t + \varphi_2) \quad (3)$$

$$v_3(t) = V_3 \sin(\omega_{sig}t + \varphi_3) \quad (4)$$

where V_0 , φ_0 are the magnitude and phase of the transmitted signal, V_1 , φ_1 ; V_2 , φ_2 and V_3 , φ_3 are the magnitudes and phases of the received signals from the three receivers, respectively and the $\omega_{sig} = 2\pi f_{sig}$ is a signal circular frequency.

To simulate different battery conditions, a potentiostat is employed to manipulate parameters such as charge and discharge capacity as well as voltage. The output of this process forms the dataset, which is time-domain signals. The transmissometry time-domain signals is represented by $v_1(t)$ while $v_2(t)$ and $v_3(t)$ represent the diffracted and reflected time-domain signals, respectively.

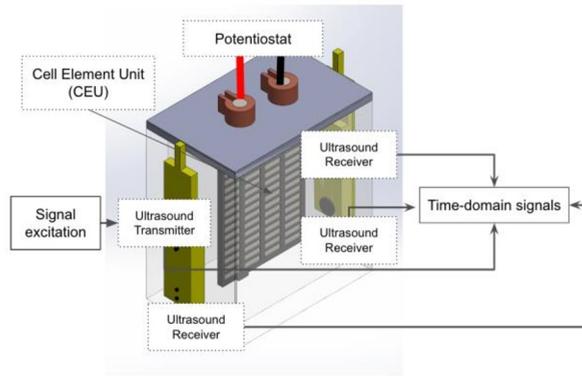


Fig. 1. Experimental Setup for Data Acquisition

Fig. 2 illustrates the framework used to develop the neural network classifier. During the data pre-processing stage, the time-domain signals undergo standardization. Subsequently, seventy percent of the data is used for training and thirty percent for testing. These standardized signals are then utilized to develop a data-driven State of Health (SoH) classification model using a neural network. The model incorporates two features: Total Harmonic Distortion and Phase Difference.

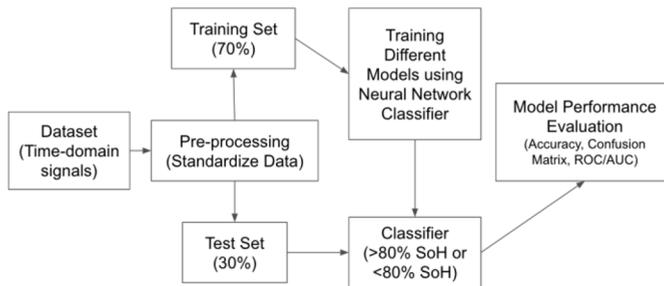


Fig. 2. Development Framework for Neural Network Classifier

As illustrated in Fig. 3, the calculation of Total Harmonic Distortion (THD), which serves as a measure of signal distortion, is accomplished by relating the harmonic frequencies to the fundamental frequency through the following equation:

$$THD = \sqrt{\frac{V_2^2 + V_3^2 + \dots + V_n^2}{V_1^2}} \quad (5)$$

where V_n represents the amplitude of the n^{th} harmonics in the frequency domain and $n=1$ is the fundamental frequency. The process begins by converting the time-domain signals into their equivalent frequency-domain signals utilizing Power Spectral Density (PSD). The fundamental frequency is identified by locating the highest magnitude frequency within the signal. This fundamental frequency serves as the basis for the computation of the harmonics. Only the first five harmonics present in the input signal are considered in this study. As a fundamental assumption, it is postulated that the amplitude of each of these harmonics, and consequently, the THD values, exhibit variations in correspondence with the deterioration of the battery's SoH.

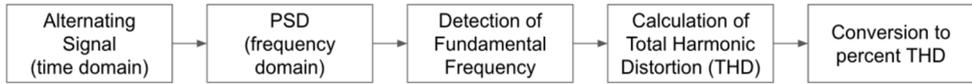


Fig. 3. Derivation of Total Harmonic Distortion (THD)

To gather information about Phase Difference (PD), this paper follows the steps shown in Fig. 4. Initially, the constant component (DC) is eliminated from the signals. Subsequently, a Hanning (Hann) window is employed to enhance frequency information accuracy. Then, Fast Fourier Transform (FTT) is performed to transform the original signal from the time domain to the frequency domain. Finally, the PD is computed by comparing the phase of the fundamental harmonics present in the signals from the transmitter and receiver.



Fig. 4. Derivation of Phase Difference (PD)

3 Results and Discussion

Several model types with various configurations were developed to derive the best classifier for the given dataset, as shown in Table 1. The neural network modeling was performed in MATLAB installed in a computer with a 1.1 GHz dual-core i3 processor and 8 GB memory. The data was standardized for all the model types, the iteration limit was set to 100, and ReLU was used as an activation function. Among these different model types, TNN exhibits an accuracy of 76.9% based on test results. This result shows a significant improvement as previously demonstrated in [10].

Table 1. Accuracy Result for Different Model Types

Model Type	Configuration	Test Result (Accuracy)
Narrow Neural Network (NNN)	One (1) fully connected layer with a layer size of ten (10)	61.5%
Medium Neural Network (MNN)	One (1) fully connected layer with a layer size of twenty-five (25)	53.8%
Wide Neural Network (WNN)	One (1) fully connected layer with a layer size of one hundred (100)	53.8%
Bilayered Neural Network (BNN)	Two (2) fully connected layers with size of ten (10) each layer	69.2%
Trilayered Neural Network (TNN)	Three (3) fully connected layers with size of ten (10) each layer	76.9%

The confusion matrixes of TNN and BNN are depicted in Fig. 5. A TNN yielded a much higher 76.9% test result accuracy than a BNN. When considering batteries with an SoH greater than 80% (interpreted as healthy batteries), the True Positive Rate (TPR) is 75%, indicating that 75% of the healthy batteries were correctly classified. The False Negative Rate (FNR) is 25%, meaning that 25% of the healthy batteries were incorrectly classified as unhealthy. Conversely, for batteries with SoH less than 80% (interpreted as unhealthy

batteries), the TPR is 78.6%, indicating that 78.6% of the unhealthy batteries were correctly classified, and the FNR is 21.4%.

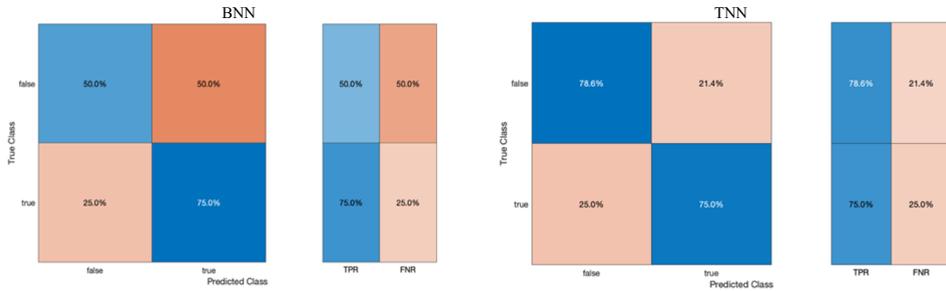


Fig. 5. True Positive Rate (TPR) vs. False Negative Rate (FNR)

As illustrated in Fig. 6, the TNN classifier's current Receiver Operating Characteristic (ROC) curve is depicted as (FPR = 0.25, TPR = 0.79). On the other hand, the Area Under the Curve (AUC) is 75%, which means the classifier exhibits good quality in differentiating the two classes defined in this study.

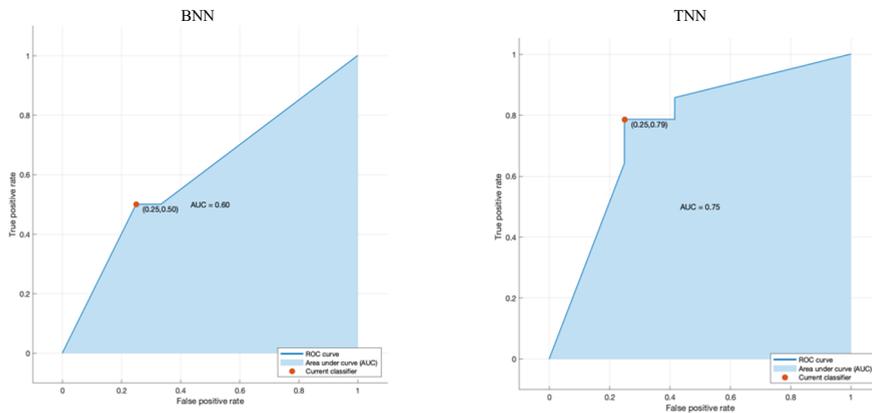


Fig. 6. AUC-ROC curve

4 Conclusion

The neural network classifier introduced in this paper derived from signals produced by ultrasound transducers showed the capability to significantly distinguish between a healthy and non-healthy lead acid battery. Ultrasonic interrogation is a non-invasive technique of data acquisition used in this study. The accuracy of this method can be attributed to the amount of data and the proper selection and processing of informative features. As lead-acid batteries continue to be used for various applications, the data-driven approach presented in this study will be significant in advancing the battery's useful life.

The authors acknowledge the support from the Technological Institute of the Philippines, Manila.

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