Neural Network – based Life Health Estimation of Valve – regulated Lead Acid Batteries

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Abstract

Load, internal resistance, ambient temperature, and discharge cycle are identified as key influencers of battery health estimation. Notably, increasing load correlates directly with a deeper discharge, demonstrating the load's impact on battery performance. Strict adherence to operational conditions, such as float voltage thresholds established by battery manufacturers, is emphasized. Batteries in stable power grid environments with limited discharge cycles are examined in this study introducing the "coup de fouet" modeling technique for accurate battery characteristic predictions during discharges. These parameters prove highly significant in estimating the useful life health of valve – regulated lead acid (VRLA batteries) [6][8]. The research highlights the importance of comprehensive understanding among telecommunications and allied stakeholders and the necessity of meeting essential requirements, including maintaining the manufacturers ambient temperature requirements and load monitoring to ensure battery performance remains within recommended thresholds.

Keywords: valve – regulated lead acid batteries; coup de fouet; health estimation; useful life; nonlinear autoregressive with exogenous

1. Introduction

Batteries play a crucial role in the process of nation-building, finding the wide-ranging applications across various industries, including broadcasting, healthcare, power generation, transportation, with a particular prevalence in the information technology and telecommunications sectors. Accurately estimating battery health is of paramount importance as it serves the dual purpose of preventing power outages and optimizing asset utilization to reduce operational costs and unplanned battery changeouts [2]. However, this presents a significant operational challenge due to the fact that battery health varies considerably under different operational conditions.

As a crucial tool for bridging gaps during grid power outages and averting service interruptions, batteries have grown in significance in the energy storage industry [1][6]. As a matter of fact, a study carried out in February 2017 by the Business Continuity Institute and the British Standards Institution brought attention to the importance of batteries. According to the research, utility supply disruptions came in sixth place and IT and telecommunications outages ranked third among the top ten global threats.

Inadequate detection of depleted batteries is the primary cause of service disruptions in the telecommunications sector, leading to revenue loss and a diminished customer experience and worst resulted to high customer churn rates [1]. A recent study in the supply chain industry, titled "Counting the Cost of Supply Chain Disruption," conducted by the Business Continuity Institute in collaboration with Zurich Insurance Group and published last November 2016, revealed significant insights. Unplanned outages in information technology and telecommunications infrastructure now rank as the top cause of disruption, rising from second place in 2015 and sixth place earlier. Most of these disruptions stem from support utilities failures caused by defective UPS batteries that uses lead acid. However, these challenges present opportunities to establish health estimation techniques and early failure mode detection, offering solutions to mitigate these issues.

Lead acid batteries with valve regulation have unique features that distinguish them from other battery types and technologies. The "coup de fouet," a phenomenon that appears at the beginning of battery discharge and is characterized by a sudden voltage drop lasting a few minutes, followed by voltage recovery to a plateau level, is a key indicator of battery health in this study [11][12]. In order to forecast the useful life health of particular valve-regulated lead acid batteries and lay the groundwork for an automated battery system, this study applies modeling techniques based on this phenomenon [2][5]. The dataset for this study was sourced from manually recorded routine maintenance records, and data was gathered from three distinct geographical locations, each with distinct parameter profiles.

The results of the study hold significant importance in the automation of battery monitoring systems, as they facilitate the anticipation of possible malfunctions and the mitigation or eradication of outages resulting from battery problems [2]. The execution of this project is expected to yield greater opportunities of savings by maximizing by better utilization of battery assets, and enhanced services to customers by avoiding possible failures through prediction modeling. The estimated useful life of valve-regulated lead acid batteries is greatly impacted by important factors such as load, internal resistance, ambient temperature, and discharge cycle [5][6]. A deeper discharge is directly correlated with higher load, and thermal aging is accelerated by higher ambient temperature, which raises the float voltage during the normalization stage. It is hypothesized that a higher float voltage lowers battery capacity. Battery manufacturers have indicated that compliance with additional operating parameters, like float voltage, is crucial [11].

Sulfation, which results from lead-acid batteries not reaching the necessary float voltage or a full charge, quickens the aging process of these batteries. Insoluble crystals gradually accumulate as a result of this happening during partial state of charge operations [3][4]. This issue is especially noticeable during grid-supplied power outages because emergency backup systems that rely on automatic transfer switches to activate cause an increase in internal resistance. Fortunately, there are methods for efficiently evaluating battery health in the event of a battery discharge during these outages. Accurate predictions of battery characteristics are made possible by the coup de fouet modeling technique, which entails utilizing the unified approach or analyzing the discharge voltage versus reserve charge characteristic [11][12].

2. NONLINEAR AUTOREGRESSIVE WITH EXOGENOUS INPUT (NARX) MODEL

Time series analysis and forecasting, neural networks are utilized in the Nonlinear Autoregressive with exogenous inputs (NARX) model [10]. Predicting future values in a time series involves combining exogenous and autoregressive inputs [3]. NARX model has the following mathematical expression:

$$y(t) = f(y(t-1), y(t-2),.., y(t-p), x(t-1), x(t-2), .., x(t-q)) \quad (1)$$

Where, y(t) represents the predicted value at time t, y(t-1), y(t-2), ..., y(t-p) are the autoregressive terms capturing the influence of past outputs, and x(t-1), x(t-2), ..., x(t-q) are the exogenous inputs. The function f represents the neural network's mapping from the past values of y and the exogenous inputs to the predicted value y(t).

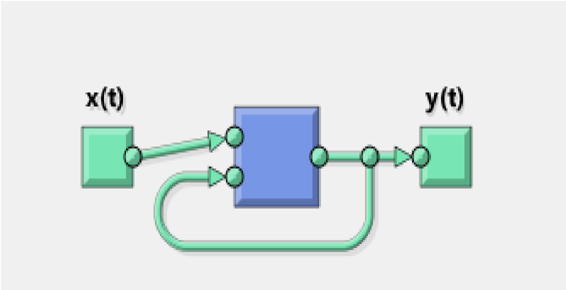

Figure 1.0 – NARX Model (Matlab R2020)

The Mean Squared Error (MSE) is a crucial metric for assessing the precision of forecasts in time series forecasting in NARX (Nonlinear Autoregressive with exogenous inputs) applications. It measures the mean squared discrepancies between observed and predicted values [10]. While a higher MSE denotes greater prediction errors, a lower MSE represents a better model fit and more accurate predictions. In order to select the best architectures and make parameter changes to improve forecasting performance, MSE is essential to the fine-tuning of NARX models [4] [10].

$$\mathrm{MSE} = \frac{1}{N}\sum_{t=1}^{N}\{y(t) - \bar{y}(t)]^2 \quad (2)$$

Where, MSE is the mean square error, N is the total number of data points in the time series y(t) represents the actual observed values at time t, y(t) represents the predicted values at time t, obtained from the NARX model [10].

NARX (Nonlinear Autoregressive with exogenous inputs) models, a reliable optimization method called the Levenberg-Marquardt training algorithm is used in this study. The convergence speed and accuracy of neural networks are improved by combining the advantages of Gauss-Newton and gradient descent techniques [10]. Through effective parameter optimization, this algorithm improves the performance of time series forecasting, specifically by minimizing prediction errors in NARX modeling by adjusting network weights [10].

$$\Delta\theta = (J^T * J + \lambda * I)^{-1} * J^T * e \quad (3)$$

Where, $\Delta\theta$ represents the change in the network parameters (weights and biases). J is the Jacobian matrix, which contains the partial derivatives of the network outputs with respect to the parameters, λ is the damping factor, controlling the trade-off between gradient descent and Gauss-Newton methods, I is the identity matrix and e is the error vector, which is the difference between predicted and actual values [10].

3. Methodology

One of the effective methods for forecasting and time series analysis is the NARX (Nonlinear Autoregressive with exogenous inputs) methodology [3]. For prediction purposes, it incorporates external variables with autoregressive elements. Battery health assessment and other nonlinear applications are examples of complex, nonlinear relationships that are captured by NARX models [10]. NARX models provide accurate forecasts and are highly adaptable for a variety of applications in diverse fields because they take into account both exogenous inputs and historical data.

The accuracy of the NARX (Nonlinear Autoregressive with exogenous inputs) model, which is set up with one hundred (100) hidden neurons and two (2) delays, is greatly affected. The model's predictive accuracy increases with the number of hidden neurons it has because it can identify more complex patterns and nonlinear relationships in the data. By incorporating two delays, the model can better capture temporal dependencies by accounting for the impact of previous time steps [3][10].

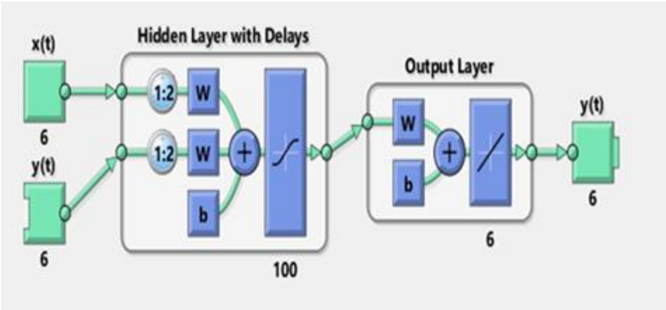

Figure 2.0 – NARX model with 100 neurons (Matlab R2020)

4. Results and discussions

The test sites situated in the three distinct geographical locations are categorized based on their grid - supplied power supply availability. Test sites are divided into three categories based on the availability of grid power: good grid area (few power disruptions); moderate availability and bad grid area (frequently experience grid-supplied power outages).

Talisay Mobile Switching Center (MSC) rectifier system or direct current (DC) power plant was built and commissioned in the year 2011. The total load is 833 amperes or 31 % utilization from the total capacity of 2,580 amperes. Supported with the two strings or banks of valve regulated lead-acid batteries FIAMM brand with the capacity of 3000 ampere-hour, float voltage charge at 20 degrees Celsius, 2.23 volts per cell. Boost recharge at 2.40 volts per cell with the maximum current of 0.25 at C10 (A) and this site categorized as good grid location. CDO MSC rectifier system or DC power plant was built and com-missioned in the year 2011. The total load is 448 amperes or 26% utilization from the total capacity of 1679 amperes. Supported with the two strings or banks of valve regulated lead-acid batteries FIAMM brand with the capacity of 3000 ampere-hour, float voltage charge at 20 degrees Celsius, 2.23 volts per cell. Boost recharge at 2.40 volts per cell

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with the maximum current of 0.25 at C10 (A) and this site represent the moderate availability location. While Iligan MSC rectifier system or DC power plant was built and com-missioned in the year 2011. The total load is 264 amperes or 14 % utilization from the total capacity of 1872 amperes. Supported with the two strings or banks of valve regulated lead-acid batteries FIAMM brand with the capacity of 3000 ampere-hour, float voltage charge at 20 degrees Celsius, 2.23 volts per cell. Boost recharge at 2.40 volts per cell with the maximum current of 0.25 at C10 (A) and this sire represent the bad grid location.

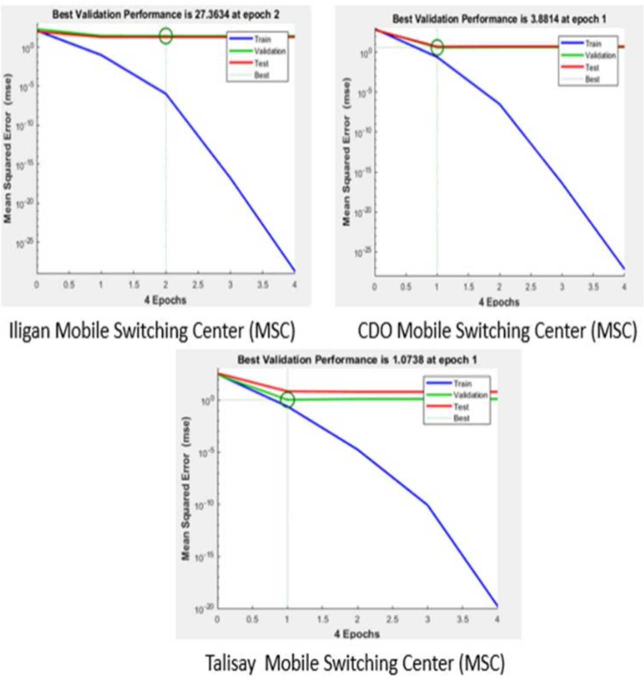

Figure 3.0 – Combined MSE for three test sites

The variation of DC loads in amperes affect other related parameters like depth of discharge. Incorporating the changes occurring due to terminal voltage, current load and internal resistance to predict electromotive force (EMF) of battery, and further estimate state of charge (SOC) based on the electromotive force [2][4][9]. Variation of loads affect other parameters such as depth of discharge and discharge cycle particularly in Iligan MSC as shown in Figure 3.0 with a record of high power interruptions. The higher the utilization experience the abrupt voltage dip within the twenty seconds of discharge or battery mode and corresponds to the increase of internal resistance of battery cells as corrosion increases because of the reduced conductivity [7]. Another contributing factor is sulfation that contributes an aging mechanism of lead-acid batteries. Due to the lack of complete full charges or not attaining float voltage state, the partial state of charge operation sulphate crystals can't be dissolved properly and crystal sulphates grow over time. This resulted to decreasing charge acceptance and increase of internal resistance over time [7].

These mean square errors suggest that other relevant parameters, such as depth of discharge, are impacted by variations in DC loads in amperes and changes brought on by internal resistance, current load, and terminal voltage to predict the battery's electromotive force (EMF) and further estimate SOC based on the electromotive force [2][9]. Other parameters, like the discharge cycle and depth of discharge, are impacted by variations in loads. The greater the utilization, the more abruptly the voltage drops during the twenty seconds of battery mode or discharge.

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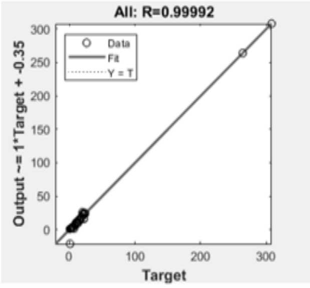
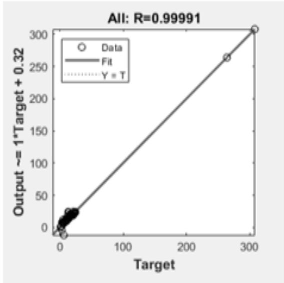
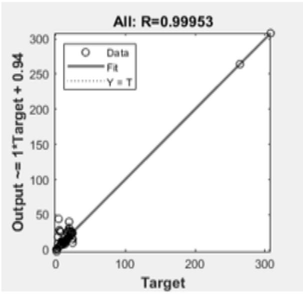


Iligan Mobile Switching Center (MSC)



CDO Mobile Switching Center (MSC)



Talisay Mobile Switching Center (MSC)

Figure 4.0 – Combine training regression plots

Increases in a battery's ambient temperature can offer status of health (SOH) data. This has a low to medium reliability because the temperature rise is small in comparison to the corresponding reduction in SOH, frequently rising only after the SOH has substantially diminished due to accelerated thermal aging. As the temperature rises, the float current rises as well, resulting in a reduction in battery capacity [4]. The data analysis correlates coup de fouet modelling technique as to ambient temperature [12]. Exposure of these batteries operational over a long period of time degrades manufacturers designed estimated useful life as data analysis shows highly significant results and this is supported by the R-value which is close to 1 (Figure 4.0) suggests a strong linear relationship between actual and predicted values, indicating a good model fit [4].

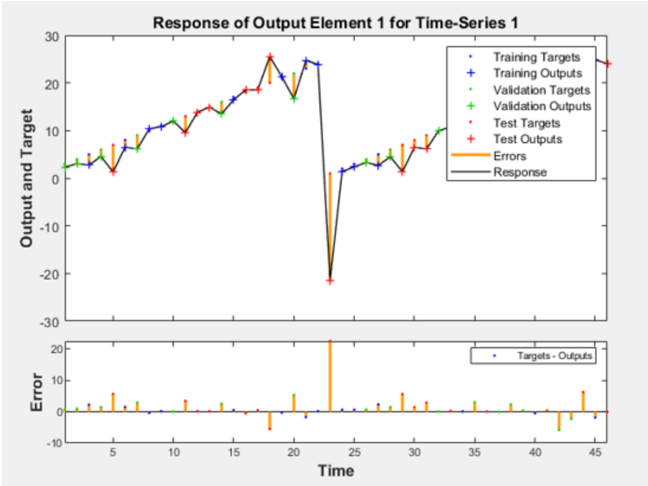


Figure 5.0 Iligan MSC time series plot response

Figure 6.0 CDO MSC time series plot response

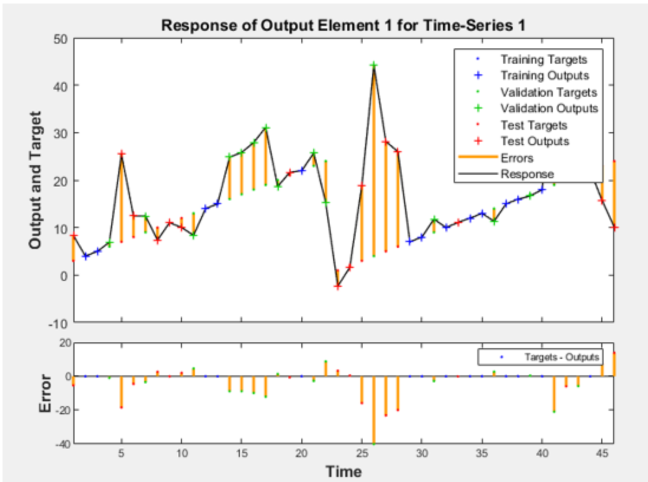


Figure 7.0 Talisay MSC time series plot response

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The data analysis though prediction & estimation technique through NARX modeled the significant parameters identified to the useful life health estimation of valve-regulated lead acid batteries. Figure 5, 6 and 7 shows the time series plot response model performance on training, validation, and test data, identifying areas of strength and weakness. Significant values and parameters help in assessing the model's fit, generalization, and error patterns, ultimately guiding adjustments for improved model performance. Considering all parameters the data analysis shows highly significant results graph, it suggests that during battery discharge operation there is an abrupt decrease of voltage from float which 53.52Vdc until it reaches plateau region until it slowly decreases, this is a coup de fouet phenomenon which unique to valve regulated lead acid batteries only. The indication of non-linearity on the scale – location graph corresponds to an abrupt voltage drop lasting a few minutes, followed by a voltage recovery to reach the plateau value, which is the modelling technique used to predict the useful life health estimation of identified valve regulated lead acid batteries [5][11][12].

5. Conclusion and recommendation

Valve- regulated lead acid batteries (VRLA), a type of batteries frequently used in telecommunications industry [8]. Valve - regulated lead acid batteries compare to other types and battery technologies has a unique characteristics which an indicator of battery state of health – the coup de fouet (a phenomenon which occurs at the beginning of the discharge of battery, it corresponds to an abrupt voltage drop lasting few minutes then, the voltage recovers to reach the plateau value) which is the modelling techniques used in this study to predict the useful life health estimation of identified valve - regulated lead acid batteries as bases to build an battery automated system [6][12]. Identified battery parameters gathered from a maintenance record manually recorded through identified routine maintenance as dataset of this study. Finally, the result of the study will be used as an important contribution to automate battery monitoring system as a tool to predict potential failures and basically eliminate or reduced outages related to battery failures. Realizing this project would increase revenue through maximizing battery assets and improved services.

Measures to be considered in the battery life cycle are airconditioned battery rooms based on the battery manufacturers recommended ambient temperature and ensure to set correct float voltage during commissioning. Monitor load threshold and do not exceed same with the per cell battery resistance through battery tester. To prevent battery sulfation, it is highly recommended to conduct constant current discharge test (CCDT) periodically after five years of operation.

Future research should look into whether this technique can be used to measure capacity decline due to ageing and other deterioration causes, such as taking into account like exposure to low temperatures and low atmospheric pressure (build in high altitude sites or during transport). Regardless of the investigation's effectiveness, this technique will serve as a guide for stakeholders to have a fundamental understanding of VRLA technology.

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Author contributions

Conceptualization [E.P.C.; M.G.C.]; methodology [E.P.C.; M.G.C.]; validation [E.P.C.; M.G.C.]; formal analysis [E.P.C.; M.G.C.]; investigation [E.P.C.; M.G.C.]; resources [E.P.C.; M.G.C.]; data curation [E.P.C.; M.G.C.; writing—original draft preparation [E.P.C.; M.G.C.; writing—review and editing [E.P.C.; M.G.C.]; visualization [E.P.C.; M.G.C.]; supervision [E.P.C.; M.G.C.].

All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declares no conflict of interest

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