Journal of Energy Storage 18 (2018) 467–475

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Life cycle prediction of Sealed Lead Acid batteries based on a Weibull model

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ARTICLE INFO

Keywords:
Statistical analysis
Life cycle
Distribution analysis
Reliability
Prediction
Weibull
Anderson–Darling
Accelerated aging
Lead-acid

ABSTRACT

The performance and life cycle of Sealed Lead Acid (SLA) batteries for Advanced Metering Infrastructure (AMI) application is considered in this paper. Cyclic test and thermal accelerated aging test is performed to analyze the aging mechanism resulting in gradual loss of performance and finally to battery's end of service life. The objective of this study is to confirm design concepts, find the life characteristic and develop standard information on failure rates and mechanisms. Reliability assessment of the SLA is evaluated using different parametric distribution analysis models and best fit distribution is selected based on Anderson–Darling adjustment value. Shape parameter (β), scale parameter (α) and threshold parameter (λ) of the selected Weibull distribution is computed from experimental cycle life test data. Thermally accelerated aging test of SLA is performed and analyzed. Failure times are extrapolated to predict the lifetimes at the desired operational field temperature.

1. Introduction

Lead acid (LA) batteries are still widely used in different small and large scale applications along with Lithium-ion (Li-ion), Nickel-Cadmium (NiCd) batteries [1]. Despite competition from Li-ion batteries, LA batteries still enjoy a large market share in utility applications and even in the current smart grid infrastructure [2]. The LA battery used in this paper will be referred as Sealed Lead Acid (SLA) cells. Its application resides as a back up battery unit with Access Points (APs) and Relays as part of the Advanced Metering Infrastructure (AMI). An AP connects smart endpoint devices with utility's Command and Control Center (CCC) providing communications to and from its Network Interface Card (NICs). It delivers reliable communication by routing all inbound and outbound network traffic, usage and metering data between smart endpoint devices and utility's CCC [3]. AP communicates directly with smart endpoint devices when they are in range and indirectly by using one or more Relays. In addition, the AP serves as a charger with a fixed current and a temperature compensated fixed voltage to the battery unit. The battery is remote from the charging circuit and is connected to the AP with a six to ten foot long cable as shown in Fig. 1. A temperature sensing thermistor is located inside the battery box and is intended to adjust the battery float voltage with the battery box temperature. The battery charger's float voltage is compensated based on the battery's temperature to maximize float life. Reliability of these batteries is stringent due to AP's significant role as a central link between endpoint devices and utility's critical systems. New generation APs have the capability of sending battery health status to utility's CCC when the capacity is exhausted as opposed to the older models. However, the cost associated with migration to new generation APs is enormous compared to analyzing the overall reliability of the back up battery units to predict their end of service life.

State of Charge (SOC) and State of Health (SOH) are two most common terms used to describe the overall status of a battery at anytime [4]. SOC shows the available capacity of the battery whereas the SOH is an indicator of the battery's ability to store and supply energy over a period of time [5]. Different methods of SOC and SOH estimation exist for LA batteries such as ampere-hour counting, voltage method, impedance spectroscopy and various other heuristic approach of charge-discharge curves [6,7]. In [8] fuzzy modeling is used to characterize the relationship between Open Circuit Voltage (OCV), SOC and discharge current. Artificial neural network is implemented to predict the SOH of LA batteries in electric vehicle and renewable energy hybrid systems applications [9,10]. In [11,12], genetic algorithm is used to model the internal characteristics of LA batteries. Modified Weibull distribution for unspecified battery chemistry is used in [13] to improve operational time and system reliability. Accelerated life data of LA batteries were used to model the life cycle based on Weibull distribution [14] and propose a new battery design for electric vehicle application. Life cycle modeling of Li-ion batteries using Weibull distribution is used in [15,16] to assess the reliability parameters. Similar work has been done in [17] where nonlinear regression model is used to determine the remaining life of Valve Regulated LA battery by modeling the relationship between capacity depreciation and aging. Due to the field application of the SLA batteries considered in this paper,

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https://doi.org/10.1016/j.est.2018.06.005
Received 5 March 2018; Received in revised form 6 June 2018; Accepted 7 June 2018

Fig. 1. Access point with backup SLA battery on a distribution line.

temperature is a key factor in the degradation of lifetime capacity. It is discussed in detail in Section 5 of this paper. The SLA batteries undergo thermally accelerated aging to simulate a lifespan of ten years and their lifetimes are predicted under field condition temperature. Similar work has been done in [31] for Li-ion batteries using holistic aging model to predict their lifetimes. Life cycle of induction motors at field temperature condition is predicted in [18] by using the Arrhenius relation on the accelerated aging failure data. Although a large body of research exist in the areas of distribution analysis for battery life cycle prediction specifically using Weibull model, most are catered to the Li-ion and NiCd batteries [15,16,28,31]. The works on lifetime prediction for LA batteries using Weibull model exist but are limited to renewable energy, electric vehicle and telecommunication applications [13,14,29,30]. The objective of this paper is to analyze the SLA battery lifetime in specific use for APs and Relays to improve system reliability and design maintenance improvements for a utility's smart grid infrastructure. It compares different distribution analysis to model failure life cycle data of SLA batteries tested based on AP and Relay's operational parameter. In addition, accelerated aging data was modeled to predict float life of the batteries under field operational temperatures. Data was collected both from experiments designed in the laboratory and the field.

This paper is organized as follows: Section 2 presents the two critical stressors that were discovered in the overall SOH assessment of SLA batteries. Section 3 describes reliability theory and the mathematical framework for the life distribution used in the experimental data and life cycle analysis on Section 4. Section 5 presents accelerated life testing and analysis under high temperature.

2. Shelf and service life stressors

2.1. Self-discharge

Batteries have stringent requirements on their shelf and operational life due to their complex chemistry [29]. Through time their expected life is reduced by various conditions such as excessive discharge–charge cycling, temperature, and improper storage and handling leading to self-discharge and sulfation. To evaluate the proper maintenance and storage practices, OCV and shelf life condition of batteries were carefully studied. OCV data was collected on all the sampled batteries before undergoing cycle life tests. The average OCV recorded for the batteries was 12.73 V at the time of arrival. Fig. 2shows the deviation of each measurement from the nominal voltage of 12.84 V. SLA battery's OCV can be correlated to its SOC [21,23]. A battery with 100% SOC has OCV reading at 12.84 V provided it has not been charged or discharged in the previous 24 h.

OCV of a battery should be regularly checked if it is being stored for long duration of time. During the preliminary investigation into the storage practices, it was discovered that batteries were kept in storage at higher temperature exceeding the recommended 25 °C for indefinite duration of time without any refreshing charge. This has led to a rapid self-discharge and shorter life span in the field for the batteries. This is evident as shown in Fig. 3 based on historical data collected on failed SLA batteries from the field averaging 12 months in storage. The rate of self-discharge is dependent on both the chemistry and temperature at which the battery is stored [21,29]. Self-discharge is a phenomenon when batteries are left in open circuit standby mode for a long duration of time resulting loss of charge over time [20,21]. If the capacity loss is not compensated by recharging in timely fashion, the battery capacity may become irrecoverable due to irreversible sulfation. Sulfation occurs when the active materials from the positive and negative plates are gradually converted into lead sulfate, making the chemistry electro-inactive [21,29]. Key factor influencing self-discharge rate is elevated temperature. To alleviate such issues, IEEE std. 450 [22] recommends a refreshing charge every 6 months for batteries kept in storage. On average, SLA batteries lose about 30–40% capacity after one year of storage when kept at 20 °C [20,21]. If there is a need for long-term storage, it is highly recommended batteries are periodically charged; typically once every 6 months [22,23].

2.2. Temperature

Temperature is one of the critical variables that affect the SOH of a battery. Lifespan of SLA batteries drops to a half incrementally for every 8 °C above the recommended 25 °C storage temperature [19,21]. However the challenge comes when accounting for erratic temperature variation rather than continuous operation at a specific temperature. Short sporadic temperature variation ages battery faster [24] than a continuous temperature condition. The SLA batteries considered in this paper are being used at a warmer location with average temperature at 29 °C. To understand variable temperature effect on the SLA batteries when the time period is known, Eq. (1) can be used to calculate the remaining life of the batteries. The equation is empirically derived from the temperature effect on battery's life.

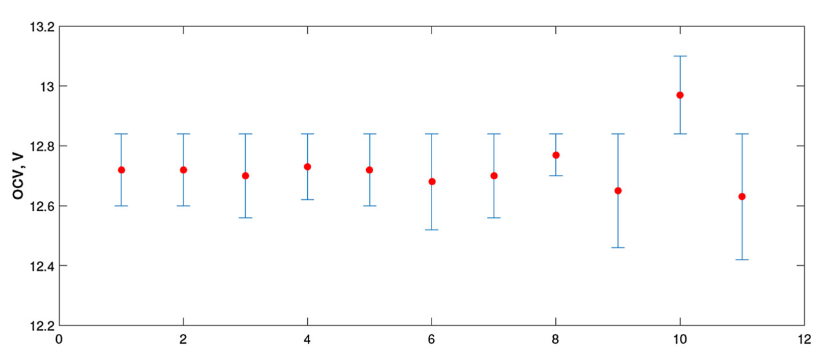

Fig. 2. Measured OCV of new batteries.