Modeling Discharge Characteristics for Predicting Battery Remaining Life

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***Abstract*—Due to the global energy crisis and air pollution, the demand for electric vehicles (EVs) and battery storage systems grows at a gallop. To support this growth, it is important to have an effective exploitation of electrochemical based energy storage system with a reliable battery management system (BMS). The remaining useful life (RUL) prediction and estimation of different age batteries are necessary for BMS design. Terminal voltage, current and surface temperature are three main types of data that have significant impacts on predicting the battery's RUL. In this paper, a mathematical model based on regression analysis is formulated to estimate the batterys RUL. Additionally, the corresponding relationship between discharge curve and battery's age is analyzed base on the battery's capacity variety with using time. Finally, the proposed model is validated with experiments on valve-regulated lead acid (VRLA) batteries.**

***Index Terms*—Energy Storage, Valve-Regulated Lead Acid Battery, Battery Management System, Remaining Useful Life.**

I. Introduction

Batteries are vital power resources for most of electrical systems. Battery failure can lead to the operation loss, interruption, and whole system malfunctioning, which can cause disastrous consequences for the system. Therefore, applying some prognostic methods to precisely predict the battery failure time is extremely recommended. These prediction tools can have a significant effect on maintenance plans of the system as well. Conventionally, most of prognostic tools concentrate on battery RUL prediction using advanced mathematical techniques such as Bayesian theories, Moving Averages, Neural Networks, and Kalman Filters [1]-[3].

The big-scale battery unit is a key part of renewable applications and electric vehicles. There are many environmental and operational factors such as temperature, humidity, chemical changes, charging/discharging rate, number of charging /discharging cycles, time duration, usage arrangements, load stages, etc. They all can lead to change (mostly increase) in ohmic values of the battery, or decrease in the battery capacity. Constant monitoring of these changes, and other battery characteristic parameters over time, plus recording data points and trend, can largely help to indicate battery replacement time, end of life of the battery, State of Charge(SOC), State of Health(SOH), and at last, the RUL of the battery.[1] Predicting the RUL of the battery precisely is the basic issue for efficient and intelligent BMS. Valve Regulated lead acid (VRLA) battery is extensively used throughout the uninterruptible power systems (UPS) as a backup energy storage systems [4]. In most cases, the VRLA battery is the only back up energy source and is critical to the defense of system failure and unreliability. BMS have garnered an increased interest and has been utilized in many applications such as EVs and electronic devices. However, the challenge lies in accurately depicting the battery capacity while minimizing the degradation effect.

Estimating battery capacity has long been the target of researchers to find the definitive RUL of a battery. Battery is considered to be at the end of its operational life when the capacity reaches 80% of its rated capacity [5]. However, knowledge of the capacity does not guarantee accurate reserve life information [6]. Although State of Charge (SOC) and remaining life are widely used to determine the status of the battery, they give little detail into the health condition of the battery [7],[8]. This affects in the long run the reliability of the battery in critical load scenarios. Frequent monitoring of battery ohmic values and other battery measurement parameters help maintain SOH, SOC and allow for prediction of RUL. SOH indicators are critical in estimating RUL of a battery since it gives insight to the degradation portfolio a battery [9],[10]. Several methods have been developed to estimate the SOH of a battery [11]. They can be classified in to three types. The first one which is the most common and popular method is capacity. The capacity method rule is when the battery reaches 80% of its rated capacity, the battery has generally failed. The second SOH indicator is the Coup de fouet phenomenon specific to lead acid battery, which occurs at the beginning of discharging stage. The last method is the impedance technique where it monitors impedance measurements of VRLA battery as it ages which tends to get higher. In [4], RUL of VRLA battery is estimated with a rule based system through the use of accumulated thermal stress, capacity trend and SOH indicators. Genetic algorithm has also been implanted for SOC and SOH estimator in [12] to predict the RUL in lead acid battery. In addition, various other modeling techniques have been used such as Bayesian theories, neural networks, Kalman filters and moving averages for RUL prediction of VRLA battery [13].

In this paper, a mathematical method is proposed to predict the battery's RUL by using the capacity change and the dis-

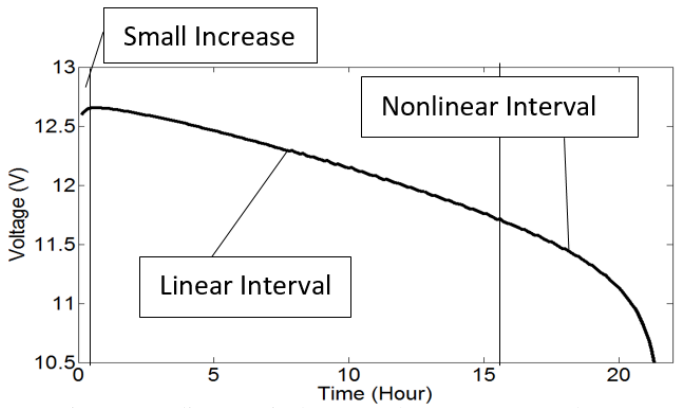


Fig. 1: Ordinary Discharge Voltage Curve(Cycle 1).

charge characteristics of each cycle. This model can be used to plot the discharge curves in different aged batteries and obtain the net change in capacity. In addition, it estimates the output voltage of the battery based on a mathematical formula, to understand aging effects of a battery on its output characteristic with the output characteristics, the model of battery's life curves can be easily built, and RUL can be estimated.

The rest of paper is organized as follows. In section II, the mathematical method is presented and the discharge characteristics model is built based on the method. In section III, the model is verified with experiment conducted on VRLA batteries. Further discussions about the factors that influence batterys RUL and discharge characteristics are included.

II. Modeling Battery's Discharge Characteristics

A battery is designed to keep a constant discharge voltage (V) to make sure the electrical appliance remains at working voltage range. At the fixed discharge current (I), the battery's terminal voltage varies with time (t) following a specific pattern. The essential battery's terminal voltage curve can be divided into three intervals by the characteristic varies with time, as shown Fig. 1, including small increase, linear interval, and nonlinear interval.

While connected to a constant current load, the battery will start with a small increase due to the internal resistance's. Since the beginning increase occupies in a small period compared to the whole discharge time, it is not considered in this paper. Due to the nonlinear nature of battery, the discharge curve is generally nonlinear with time, and the linear interval varies in different time periods. Therefore, in this model, the discharge curve is modeled in linear and nonlinear intervals, respectively. After the highest voltage level, the battery's discharge curve keeps approximately linear drop up to the knee point. For the linear interval, in order to estimate the relationship between the battery's voltage (V) and time (t), as shown in [14], the N-order polynomial regression can be used to fit data points to the following equation:

$$V(t) = \sum_{i=0}^{N} A_i t^i + \varepsilon, \tag{1}$$

where N is the degree of the polynomial model, and ε is an unobserved random error with mean zero conditioned on a scalar variable. The goal of the polynomial regression is to determine values for the parameters $A_i, i \in \{0, ..., N\}$ that make the estimations best fit the curve. Due to the battery's discharge curve captures a long period where V is approximately linear with t, in this paper, the order of Equation (1) is set to 1. Then, the voltage function $\Gamma : t \to V$ can be defined as $V(t) = A_1 t + A_0 + \varepsilon$, where A_1 denotes the negative correlation between V and t, and A_0 denotes the initial voltage. Additionally, A_1 and A_0 are impacted by the discharge cycle number (c) of the battery and the battery's self-characteristic.

When we extend the estimation model to the whole discharge curve, we can find a nonlinear drop at the final stage indicating the battery is almost empty. Therefore, a nonlinear regression model is formulated as follows:

$$V(t) = A_1 t + A_0 + f(t - t_D) + \varepsilon, \tag{2}$$

where t_D is the beginning time of the nonlinear interval, and $f(t - t_D)$ is a nonlinear function depicts the nonlinear interval of the discharge curve from time t_D. In this model, the nonlinear function f is described by the exponent elements with time offsets to the linear regression model, as $f(t - t_D) = -e^{-[a_1(t-t_D)+a_0]}$, where $[0, t_D]$ is the period of the linear interval, and the remaining time is the period of the nonlinear interval. a_1 is determined by the decrease shape of the battery's curve, and a_0 is determined by the error at time t_D between the data point and the linear estimate. Since the error at t_D between the data point and the linear estimate is enough small, a_0 could be ignore. So the final fitting equation can be formulated as follows:

$$V(t) = A_1 t + A_0 - e^{-[a_1(t-t_D)]} + \varepsilon, \tag{3}$$

where, A_1 and A_0 are parameters set to determine the linear intervals of discharge voltage curve; a_1 is the parameter set to determine the natural logarithm of the inaccuracy for nonlinear intervals. The knee point t_D is the time migration of the exponent elements, and it is the extent of the linear intervals in value. Additionally, all the parameters are impacted by the discharge cycle number (c) of the battery and the batterys self-characteristic. The relationship between parameters and the discharge cycle number of the battery will be analyzed in next section.

The goal of the nonlinear regression model is to determine values of the parameters A_0, A_1, a_1, and t_D that minimize the sum of the least square of the distances of the data points to the derived estimates. The method of least square is implemented for approximating these parameters. Let V_{real} denote the real voltage data point, and $V(t)$ denote the nonlinear voltage estimation model. The optimal parameters A_0^*, A_1^*, a_1^* can be derived by solving the following problem:

$$\min_{A_0, A_1, a_1} SS = \sum_{t \in T} r^2(t) = \sum_{t \in T} [V_{real}(t) - V(t)]^2, \tag{4}$$

where T denotes the time period for a discharge cycle. By minimizing this function, we first assemble the individual

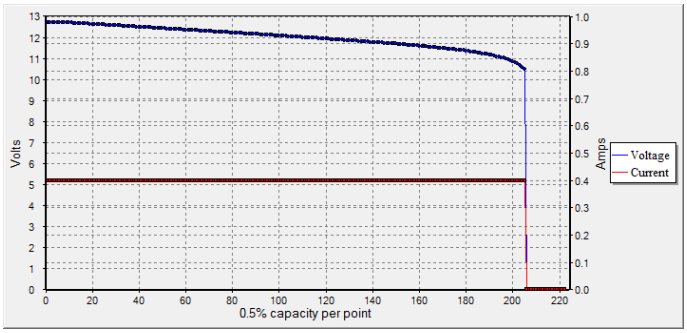


Fig. 2: The discharge current and voltage curve shown at GUI.

components $r(t)$ from (4) into a residual vector $r : R^3 \rightarrow R^T$ defined by

$$r(A_1, A_0, a_1) = (r(1), r(2), ..., r(T))^T. \quad (5)$$

Using this notation, we can rewrite SS as $\|r(A_1, A_0, a_1)\|_2^2$. The derivatives of SS can be expressed in terms of the Jacobian of r, which is the $T \times 3$ matrix of first partial derivatives defined by

$$J(A_1, A_0, a_1) = [\frac{\partial r(t)}{\partial A_1}, \frac{\partial r(t)}{\partial A_0}, \frac{\partial r(t)}{\partial a_1}]_{t=1,..T}. \quad (6)$$

We have

$$\bigtriangledown SS(A_1, A_0, a_1) = J(A_1, A_0, a_1)^T r(A_1, A_0, a_1). \quad (7)$$

$$\bigtriangledown^2 SS(A_1, A_0, a_1) = J(A_1, A_0, a_1)^T J(A_1, A_0, a_1) + \sum_{t \in T} r(t) \bigtriangledown^2 r(t). \quad (8)$$

Therefore, the optimal parameters A_0^*, A_1^*, a_1^* can be derived by calculating (7) and (8).

In the test procedure method, the constant current is obtained by supplying it to the discharge battery. The battery is discharged by controlling the end of discharge voltage (EODV) and charging current to zero, shown as Fig.2. The battery's capacity is defined by the discharge current i_{bat} and the discharge time t.

$$C_n = (\int i_{bat}\ dt)/3600 \quad (9)$$

III. Verification

In practical applications, the estimations of the model parameters can be obtained based on the discharge curves of different battery ages (cycles). According to the relationship between model parameters and battery ages (cycles), all parameters can be estimated by a given battery age (cycle).

A. Experiment setup

The experiments have been carried out on the same batch 12V 8000mAh VRLA Battery made by ENERSYS-CYCLON of capacity 8000 mAh and nominal voltage of 12 V to validate the above approach. The cells have been cycled (charging and discharging) using PCBA 5010-4 battery analyzer having channel voltage range from 0 V to 51 V and current range from 0 A to 10 A at -30 to +96 degrees Celsius. The connection between battery and battery analyzer is shown as Fig.3.

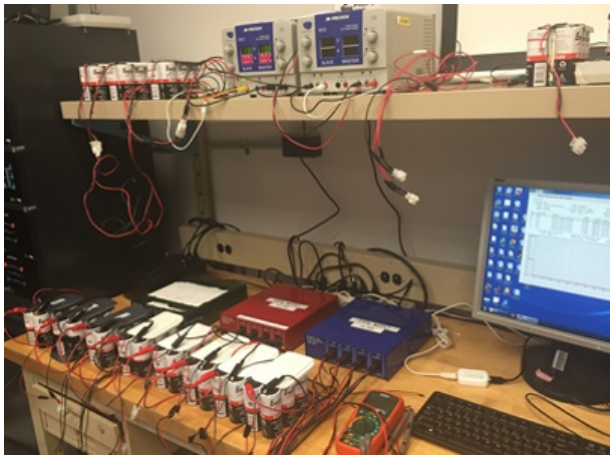


Fig. 3: The experiment test connection.

The whole system was set up at the ambient temperature of 25°C. The battery analyzer records the voltage and current curves based on the time to complete each discharging cycle, and the battery's capacity is calculated after each cycling step. The analyzer is controlled by computer by using USB connection and could be programed with a graphical user interface (GUI) application. Based on the IEEE standard and the battery manufacturer manual requirement, the cycling test was design by following steps: Charging was carried out in a constant current (CC) mode at 400 mA (0.05C) until the battery voltage reached 14.7 V and then continued in a constant voltage (CV) mode at 14.7 V until the charge current decreased to 10 mA. Discharge was carried out at a constant current (CC) level of 400 mA until the battery voltage dropped to 10.5 V(EODV). Each cycle remain more than 45 hours, and the experimental test remain 8 months, from September 2015 to May 2016, to complete 51 cycles.

Fig.4 presents the curves of discharge for VRLA battery at 11 typical cycles from cycle 1 to cycle 51. In Fig.4, we can find the discharge curve varies with different battery cycles. And the capacity of lead-acid battery is related to battery cycles, with the increase of the cycle, the beginning time of nonlinear interval will be more smaller. After the linear interval, the terminal voltage drops fast when battery cycle number is larger, and

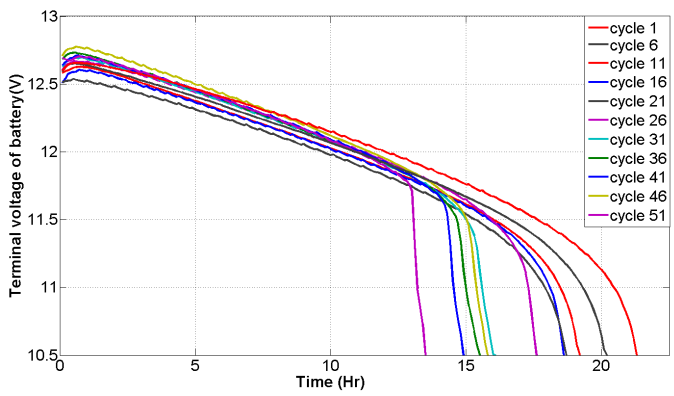
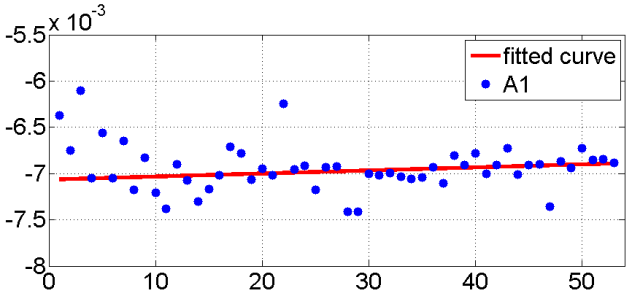
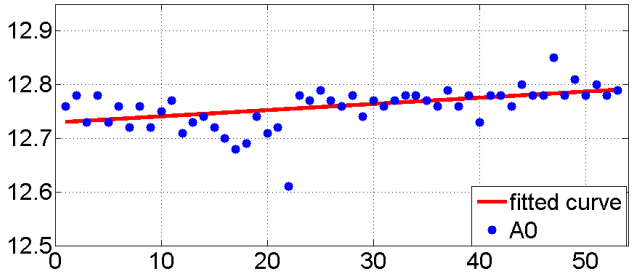


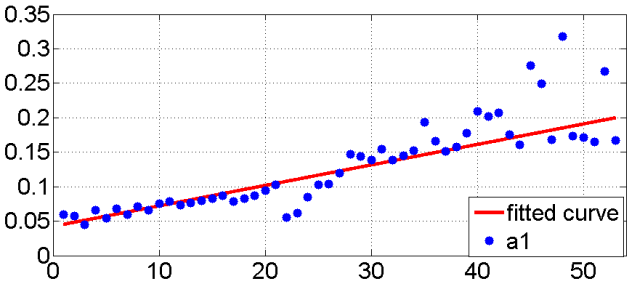
Fig. 4: The curve of discharge for VRLA battery at different ages(cycles).



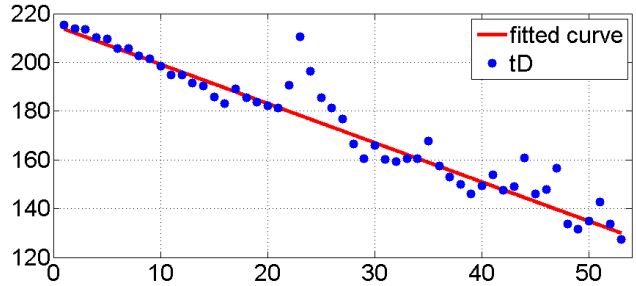
(a) $A_1 = 3.305 \times 10^{-06} \times n + -0.007067$



(b) $A_0 = 0.001155 \times n + 12.73$



(c) $a_1 = 0.002973 \times n + 0.04213$



(d) $t_D = -1.609 \times n + 215.3$

Fig. 5: Relationship between model parameters and battery cycles(n)

the capacity of the battery can release fewer. For instance, in cycle 1, the beginning time of nonlinear interval is 15 hour. However, in cycle 51, the time is decreased to almost 12 hour. This phenomenon can be explained that, large number of lead sulfate is generated to attach on the surface of lead dioxide results in the proliferation of the electrolyte being not easy when the battery cycle number of battery is large.

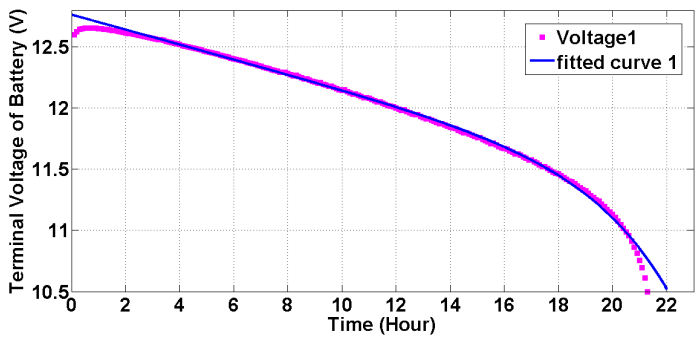
B. Battery Remaining life Prediction Model Verification

After getting 51 sets of discharge terminal voltage data, the polynomial regression fitting is implemented for training the proposed battery remaining life prediction model (3), where parameters A_0^*, A_1^*, a_1^*, t_D are derived. The average residual sum of squares (RSS), coefficient of determination (R^2) and root-mean-square deviation (RMSD) between real battery data and prediction models are shown in Table.I. From this table, we can find that the RSS and RMSD value is less than 0.2, indicating that the prediction model has a smaller random error component and a good performance. And the (R^2) value is very close to 1 indicating that a greater proportion of variance is accounted for by this model. Since the goodness of fit show the higher accuracy, the proposed model is more useful for prediction aged battery's discharge characteristic. From the Fig.6 (a), most of the big error belong to the beginning 36 mins and last 24 mins. And the largest error is less than 1% below the predict number, shown as Fig.6 (b).

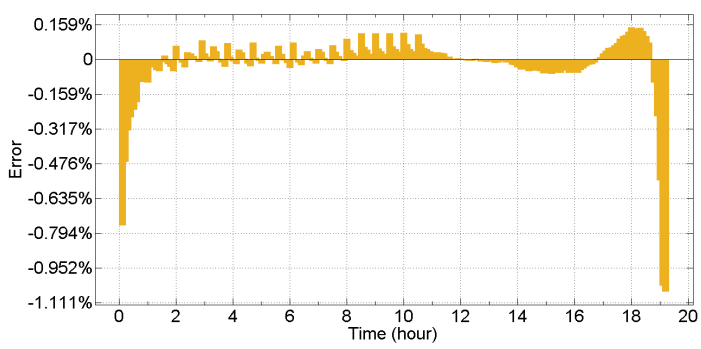
The battery's capacity is defined by the discharge current i_{bat} and the discharge time t. Because the discharge current is constant, the discharge time is linear to the battery's capacity. The proposed battery remaining life prediction model (3) gives the relationship between the battery discharge voltage V and the discharge time t. Four parameters, A_0^*, A_1^*, a_1^*, t_D, are

RSS	$RMSD$	R^2
0.16663	0.03107	0.99467

TABLE I: The average goodness of fit of single cycle.



(a) The hybrid fitting result



(b) Fitting model errors

Fig. 6: Verification of the cycle discharge model

impacted by the discharge cycle number of the battery and the battery's self-characteristic. In Fig. 5, we can find the relationship between parameters and battery cycles. From the figure, we can find the relationship between parameters and battery cycles all can be represented as linear fitting curves. However, for A_0^*, A_1^*, a_1^*, the parameter increases with the battery cycle. For t_D, the parameter decreases with the battery cycle. The average residual sum of squares (RSS), coefficient of determination (R^2), adjusted coefficient of determination (R^2), and root-mean-square error (RMSE) for four parameters are shown in Table II. From this table, we can find that the RSS and RMSD value of A_0^*, A_1^*, a_1^* has a small value indicating that the prediction model has a smaller random error component and a good performance. And the (R^2) value of t_D is very close to 1 indicating that a greater proportion of variance is accounted for by this model.

	A_1	A_0	a_1	t_D
RSS	$1.733e^{-6}$	0.0368	0.0246	1325
R^2	0.485	0.5147	0.8845	0.9602
Adjusted R^2	0.4749	0.5052	0.8823	0.9595
RMSE	0.0002	0.0269	0.0220	5.098

TABLE II: The parameter's goodness of fit

C. No.53 cycle verify the modeling method

Parameters of different battery age can be estimated with the relationship obtained in the former section. In this section, the No.53 cycle discharge curve is used to be estimated as an example to verify the modeling method in 22 degrees Celsius and 0.05C current rate, shown as table III. The prediction result is shown in figure 7. From Fig.7, the X is the real data value and the blue curve is fitted curve by using Equation (3). The red curve is predicting result by estimating the No. 53 parameter. And from this result, we can using time difference(6 mins) to get a 40 mAh capacity difference between real data and predicting value. And shows the high accuracy of this model.

TABLE III: PARAMETERS OF No.53 CYCLE DISCHARGE CURVE

Accurate parameters	Estimated parameters
A_0=-0.00688	A_0=-0.00689
A_1=12.79	A_1=12.79
a_1=0.1667	a_1=0.1996
t_D=127.3	t_D=130.0

IV. Conclusion

This paper proposes a simple method for modeling the relationship between batteries capacity change and cycling age. And get the remaining useful life based on the capacity. The prediction of RUL is an important way for BMS to monitor the health condition and manage the battery intelligently. Lots of unnecessary loss will be avoided by using the intelligently BMS to predict the RUL accurately. The proposed method can be not only used to predict the RUL of VRLA-battery but also extended in the RUL prediction of other industrial products.

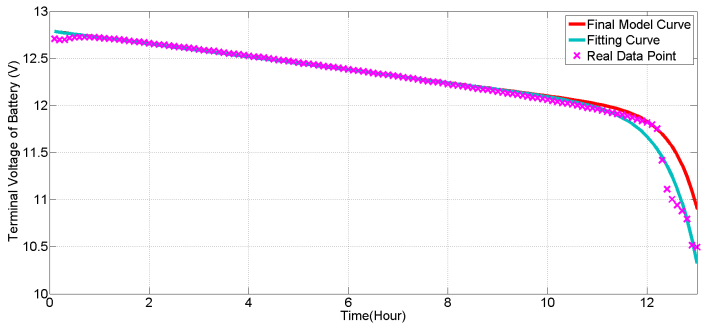


Fig. 7: Verification of No.53 cycle

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V. Reference

[1] B. Cotton, "VRLA battery lifetime fingerprints - Part 1," Intelec 2012, Scottsdale, AZ, 2012, pp. 1-8.

[2] P. Ma, S. Wang, L. Zhao, M. Pecht, X. Su and Z. Ye, "An improved exponential model for predicting the remaining useful life of lithium-ion batteries," 2015 IEEE Conference on Prognostics and Health Management (PHM), Austin, TX, 2015, pp. 1-6.

[3] Jingshan Li; Shiyu Zhou; Yehui Han, "PROGNOSTIC CLASSIFICATION PROBLEM IN BATTERY HEALTH MANAGEMENT," in Advances in Battery Manufacturing, Service, and Management Systems , 1, Wiley-IEEE Press, 2017,

[4] P.E.Pascoe, A. H. Anbuky, Standby Power System VRLA Battery Reserve Life Estimation Scheme, IEEE Transactions on Energy Conversion, Vol. 20, no. 4, 2005

[5] IEEE Recommended Practices forMaintenance, Testing and Replacement of Valve Regulated Lead Acid (VRLA) Batteries in Stationary Applications, IEEE Stand 1188, 2014

[6] Y.Sun, H. Jou, J. Wu, Auxiliary diagnosis method for lead-acid battery health based on sample entropy, Elsevier Energy Conversion and Management, vol. 50, 2009

[7] A.Vasebi, SMT. Bathaee, M. Partovibakhsh, Predicting state of charge of lead acid batteries for hybrid electric vehicles by extended Kalman filter, Energy Convers Manage, vol. 49, no. 1, 2008

[8] WX. Shen, State of available capacity estimation for lead-acid batteries in electric vehicles using neural network, Energy Convers Mange, vol.48, no.2, 2007

[9] E. Davis, D. Funk, W. Johnson, Internal Ohmic measurements and their relationship to battery capacity EPRIs ongoing technology evolution, In Battcon, 2002

[10] E. Landwehrle, Post mortem test and measurements on a VRLA battery, Battcon, 2005

[11] Y. Sun, H. Jou, J.Wu, Novel auxiliary diagnosis method for state of health of lead acid battery, International conference on power electronics and drive systems, 2007

[12] H.Chaoui, S.Miah, A.Oukaour, & H.Gualous, State of charge and State-of Health prediction of lead-acid batteries with genetic algorithms, IEEE ITEC, 2015

[13] B. Cotton, VRLA battery lifetime fingerprints- part 1, IEEE Standards Association, 2012

[14] Z. He, G. Yang, H. Geng, et al., A Battery Modeling Method and Its Verification in Discharge Curves of Lead-Acid Batteries, Vehicle Power and Propulsion Conference, 1-5, 2013