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A Rapid Capacity Estimation Method Of VRLA Batteries Based On "Coup De Fouet"

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Abstract:
Background*: The valve regulated lead acid (VRLA) batteries play a crucial role in ensuring the reliable operation of DC backup power supplies. However, traditional methods for estimating the capacity of VRLA batteries are time-consuming and labor-intensive.*
Materials and Methods*: To address this issue, this paper proposes a rapid capacity estimation method based on discharge voltage-lion swarm optimization-back propagation (discharge voltage-LSO-BP) by using the "Coup de Fouet" characteristic of the VLRA batteries. Firstly, using the existing discharge data during the first 2h to obtain the peak and trough voltages and the fitted relationship between discharge voltage and capacity as characteristic parameters. Secondly, the LSO algorithm is used to optimize the BP network, which has optimal network weights and thresholds. Finally, the VRLA battery capacity is quickly estimated based on the discharge characteristic parameters and the LSO-BP model.*
Results*: The simulations show that the RMSE of the proposed discharge voltage-LSO-BP capacity estimation model is only 1.70%, which is 4.13% lower than the conventional BP.*
Conclusion: *The model can quickly predict the capacity of VRLA batteries with high prediction accuracy, and avoiding the loss of life caused by the frequent discharge capacity testing process.*
Key Word*: Back Propagation; Capacity Estimation; Coup De Fouet; Lion Swarm Optimization; Valve Regulated Lead Acid Batteries*

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I. Introduction

In power substations, VRLA batteries are often used as DC backup power supply, which is responsible for emergency power supply to important loads. Batteries are frequently utilized as a source of direct current (DC) power, hence in the context of electrical systems, DC power systems and batteries have a very strong relationship with one another. A battery is a type of electrochemical device that can change the energy stored in chemical form into electrical form. It is made up of one or more electrochemical cells, which may or may not be connected in series or parallel in order to achieve the desired voltage and capacity. On the other hand, direct current (DC) power systems are electrical systems that get their power supply directly from the current itself. The flow of electric charge in these systems is unidirectional, meaning that it always moves from the positive terminal to the negative terminal. This characteristic is what gives these systems their name. Due to the VRLA batteries usually working at long-term floating charge and irregular discharge mode, the power supply capacity and reliable life of the batteries are rapidly depleted [1]. Therefore, to ensure sufficient emergency power supply capacity and reliability, it is necessary to study the VRLA batteries capacity estimation method. Estimating capacity is the method of calculating the maximum output or production capabilities of a system, process, or organization. It is an essential component of both corporate planning and decision-making since it assists companies in determining their production capacity, locating potential bottlenecks, and efficiently allocating resources. Estimating a company's capacity is an essential part of helping a business run effectively and efficiently. This ensures that the business will be able to satisfy the requirements of its clients while continuing to generate revenue.

In the practice of power substations, the capacity of VRLA batteries is obtained through discharge tests [2,3]. However, every capacity testing costs nearly ten hours, consuming a lot of manpower and material resources in practice. At the same time, there is a long time interval between the capacity testing every two capacity testing, which is inconvenient to estimate the emergency power supply capacity of the battery pack [4]. In addition to the direct testing method used for substation maintenance, there are two other indirect estimation capacity methods. One is model-driven method, the other is data-driven method. Constructing the model of the VRLA battery attenuation mechanism can also estimate the capacity. Common battery models include attenuation mechanism models [5], equivalent circuit models [6], and experience degradation models [7,8]. Model-based methods for estimating VRLA battery capacity are generally combined with a Kalman filter-like recursive algorithm for optimal estimation of battery capacity in a minimum variance sense after an accurate battery model has been established [9,10]. For example, Literature [11] proposed a battery prediction method based on non-traveled Carman filtering, which is higher than the particle filtering algorithm. Overall, the model-based Kalman filter method has a high detection accuracy, a strong initialization error correction capability and can effectively suppress system noise. However, this type of method is heavily dependent on the battery model and requires a hardware processor with a sufficiently fast computational speed. In addition, the data-driven method estimates the capacity by extracting attenuation characteristics from charge-discharge data. This method has high predictive accuracy and a relatively wide application range. Literature [12] improved the non-traded particle filtering algorithm and overcomes the particle degradation of particles in the standard particle filter algorithm. In literature [13], the most classical of artificial neural networks, BP neural network, was used to model and predict the battery capacity, and the models with different training functions were compared in terms of model con-vergence speed and detection accuracy. The simulation results show that the method effectively improves the accuracy of VRLA batteries capacity estimation. The development of intelligent algorithms offers new solutions for VRLA batteries capacity estimation.

However, most of the current research requires long-term charge and discharge experiments to get the capacity. As for complete charge and discharge test, the time and economic cost a lot. As for the two indirect estimation methods, also require a great deal of experimental data. the model-driven method depends on the precise models, and the model parameters are very sensitive to changes in working conditions. Thus, parameter recognition and updating requires experiments with multiple working conditions. Data-driven method is simple in operation, but it relies on a large amount of experimental data to learn the degradation laws.

In view of the time-consuming and heavy workload of the traditional VRLA batteries capacity estimation method, this paper proposes a rapid capacity estimation of VRLA batteries based on discharge voltage-LSO-BP method. Firstly, the "Coup de Fouet" phenomenon that steep drop and recovery in the early stages of discharge are captured through various floating charge tests. Then, based on the correlation between discharge voltage and capacity, the discharge voltage-LSO-BP model is constructed. Finally, the accuracy and rapidity of the proposed method are verified by five VRLA batteries samples under multiple floating charging pressures.

II. Correlation Analysis of "Coup de Fouet" with Capacity of VRLA batteries

VRLA batteries are mainly composed of positive and negative plates, separators, positive and negative poles, safety valves, electrolyte, shell and other components, the basic structure is shown in Figure 1. The negative and positive electrode of a lead acid battery is formed of porous or spongy lead and lead oxide, respectively. A sulfuric acid and water electrolytic solution is used to submerge both electrodes. An electrically insulating but chemically permeable membrane separates the two electrodes in the event that they come into contact due to physical movement of the battery or changes in electrode thickness. Additionally, this membrane shields the electrolyte from electrical shorts. The chemical reaction below, which is reversible, is how lead acid batteries store energy. The charging and discharging process of lead-acid batteries is mainly a transformation between lead and divalent and tetravalent lead.

As a whole, the chemical reaction is:

$$Pb + PbO_2 + 2H_2SO_4 \underset{charge}{\overset{discharge}{\rightleftarrows}} 2PbSO_4 + 2H_2O$$

(1)

The charge and discharge reactions at the negative terminal are as follows:

$$Pb + H_2SO_4 \underset{charge}{\overset{discharge}{\rightleftarrows}} PbSO_4 + 2H^+ + 2e^-$$

(2)

The charge and discharge reactions are as follows at the positive terminal:

$$PbO_2 + H_2SO4 + 2H^+ + 2e^- \underset{charge}{\overset{discharge}{\rightleftarrows}} PbSO_4 + 2H_2O$$

(3)

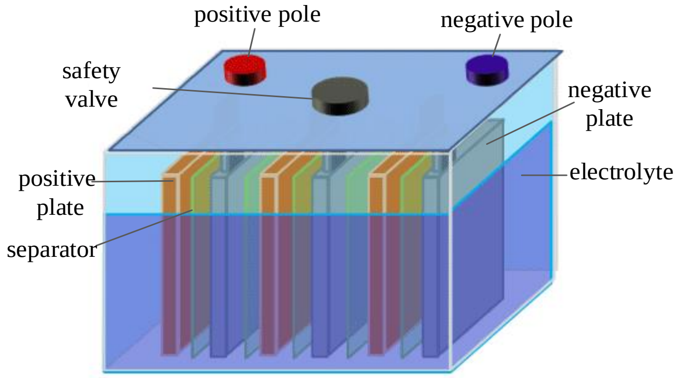


Figure 1. Basic structure diagram of VRLA batteries

"Coup de Fouet" is a phenomenon in which the voltage of a VRLA battery falls rapidly at the start of discharge, then rises briefly and then continues to fall slowly. The "Coup de fouet" phenomenon occurs because the battery is in internal equilibrium before discharge. After discharging, the active material on the surface of the positive plate comes into contact with the sulfuric acid and undergoes a chemical reaction, thus the concentration of sulfuric acid in the vicinity of the positive plate decreases, and the voltage of the battery drops rapidly. According to the principle that concentration flows from high to low, the sulfuric acid in the vicinity begins to flow slowly toward the positive plate, when the rate of sulfuric acid consumption by reaction is greater than the rate of replenishment by diffusion, the voltage will continue to fall; when the rate of sulfuric acid consumption by reaction is less than the rate of replenishment by diffusion, the voltage of the battery rises again due to the high concentration of H+. Eventually, as the reaction proceeds and the concentration of sulfuric acid decreases, the H+ concentration also decreases gradually, and thus, the voltage of the cell will continue to decrease slowly after a brief recovery.

As shown in figure. 2, the peak voltage Up and the trough voltage Ut represent the voltage at the highest and lowest positions in the process, respectively. The literature [14] shows that the "Coup de Fouet" phenomenon corresponds to the capacity of the battery, providing a new way of predicting the capacity of VRLA batteries.

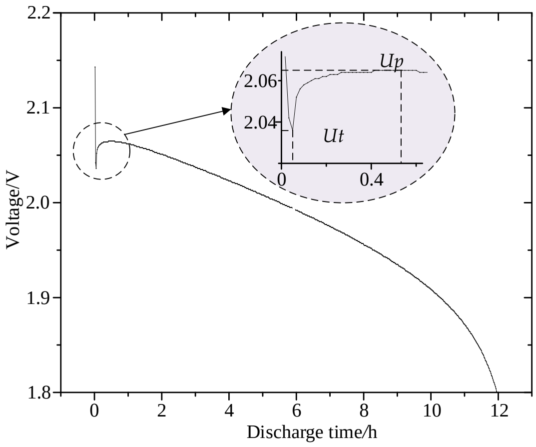


Figure 2. Coup de fouet" phenomenon during discharge of VRLA batteries

In order to further investigate the correlation between the "Coup de Fouet" phenomenon and the discharge capacity of VRLA batteries during discharge and to shorten the conventional capacity discharge test cycle, this paper designs an accelerated discharge and float cycle durability test for VRLA batteries.

The test is designed using 5 VRLA battery samples, 50°C ambient temperature, 5 float charge voltage levels and 10 days float charge cycle as shown in Table 1. The test rig consists mainly of a constant temperature and humidity chamber, VRLA battery samples, DC regulated power supply, activator, resistance tester and balance. The specific test steps are as follows:

First screening of samples and checking for consistency.

The initial capacity of the 5 specimens is determined by measuring their capacity at the discharge rate over a period of 10 hours.

Each of the five specimens is subjected to treatment at a voltage of 2.20V, 2.23V, and 2.28V in an atmosphere of 50℃±2℃. And the floating charge voltage that is steady at 2.30V for 10 days. For each sample, the floating charge current is measured and recorded.

After 10 days of continuous floating charge, the 5 samples are cooled to 25℃±2℃in the floating state, and the mass and internal resistance of each sample are measured after standing for 2 hours. Then the discharge capacity of each sample is measured by 10h rate discharge test according to the flow of capacity performance test.

When the discharge capacity of the sample is greater than 0.8C0, the specimen is fully charged and the next cycle of floating charge test is carried out according to steps 3~4.

When the discharge capacity of the sample is less than 0.8C0 the sample is fully charged and then carried out a 10h rate discharge test. If the test result is greater than 0.8C0, the sample is fully charged and the next cycle of floating charge test is continued. If the test result is still less than 0.8C0, the float durability test is over.

Table 1. Design of 50°C-five voltage levels accelerated floating charge durability experiment.

Specimen number	Float voltage	Environmental temperature
1	2.20V	50℃±2℃
2	2.23V	
3	2.25V	
4	2.28V	
5	2.30V	

III. Rapid Capacity Estimation Method of VRLA Batteries Based on "Coup de Fouet"

The regular capacity testing of station-use VRLA batteries typically requires a minimum of 10 hours, and the workload increases substantially with the number of batteries. In view of the time-consuming and heavy workload of the traditional VRLA battery capacity estimation method, according to the phenomenon of "Coup de Fouet" in the early stage of VRLA battery discharge and the correlation between discharge voltage and capacity, this chapter studies the rapid estimation of capacity based on discharge voltage-LSO-BP method.

Subsection Extraction of Feature Parameters Based on "Coup de Fouet"

In this section, characteristic parameters such as peak and trough voltages for the first 2h of VRLA batteries discharge and the fitted relationship between discharge voltage and discharge capacity are obtained.

Firstly, the discharge voltage and the discharge capacity data of the VRLA batteries are obtained in the first 2h of the capacity testing. Then, the peak voltage Up and the trough voltage Ut are selected based on "Coup de Fouet" at the beginning of the discharge period. Next, a quadratic polynomial function f=ax2+bx+c is used to fit the relationship between the discharge voltage and the discharge capacity over 2h, where x stands for the discharge voltage Up and Ut, and f stands for the discharge capacity. In the section 2, we already know that different battery capacities correspond to different Up and Ut, so it is only necessary to find the coefficients a, b, c to use this polynomial function to describe the relationship between the discharge voltage and the battery capacity.

Construction of LSO-BP Model

Description of BP Neural Network

BP neural network is a multilayer Feedforward neural network trained according to the error back propagation algorithm. The structure of a typical three-layer BP neural network model is shown in Figure 3. The relationship between the input feature vector [x1, x2, …, xi] T and the output y can be described as:

$$y=\begin{bmatrix}\beta_1 & \beta_2 & \cdots & \beta_L\end{bmatrix}\left\{\begin{bmatrix}\omega_{11} & \cdots & \omega_{1I}\\ \omega_{21} & \cdots & \omega_{2I}\\ \vdots & \cdots & \vdots\\ \omega_{L1} & \cdots & \omega_{LI}\end{bmatrix}\begin{bmatrix}x_1\\ \vdots\\ x_I\end{bmatrix}+\begin{bmatrix}b_1\\ b_2\\ \vdots\\ b_L\end{bmatrix}\right\} \tag{2}$$

where L is the number of neurons in the hidden layer of the BP neural network model; ωli (l=1, ..., L, i=1 ... I) is the matrix of weight coefficients for the i-th input neuron in the l-th hidden layer; bl (l=1, ..., L) is the threshold vector of the l-th hidden layer; the weight matrix of the input neuron ω, the threshold column vector b of the hidden layer and the weight column vector β of the neurons in the hidden layer, the initial values of which are obtained by random generation, respectively.

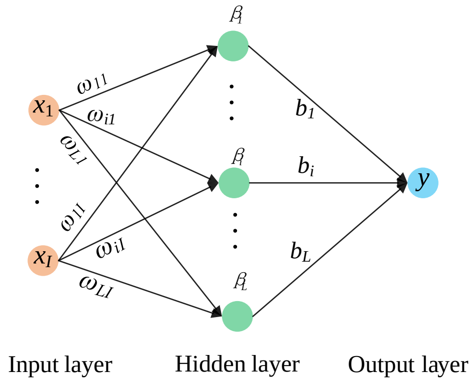


Figure 3. BP neural network structure.

LSO algorithm to optimize BP networks

The LSO optimization algorithm is a new type of swarm intelligence optimization algorithm [15].By simulating social behaviors such as hunting and reproduction of lions, a model for solving global optimal problems is established to complete the solution to complex problems [16]. The principle of the algorithm is as follows:

Suppose there is a lion group composed of N lions in the D-dimensional target search space, and the number of adult lions is n. The position of the i (1≤i≤N) lion is:

$$x_i = (x_{i1}, x_{i2}, ..., x_{iD}), 1 \le i \le N \tag{2}$$

The number of young lions is N-n, and different types of lions move in different ways during hunting. The lion king moves in a small range at the best food to ensure his privileges, and updates his position as follows [17]:

$$x_i^{k+1} = g^k (1 + \gamma \| p_i^k - g^k \|) \tag{3}$$

The lioness needs to cooperate with another lioness during the predation process, and adjust her position as follows:

$$\begin{cases} x_i^{k+1} = \dfrac{p_i^k + p_c^k}{2}(1 + \alpha_f \gamma) \\ \alpha_f = step \cdot \exp(-30t / T)^{10} \end{cases} \tag{4}$$

In equations (3) and (4), γ is a random number generated according to the normal dis-tribution N (0,1), αf is the disturbance factor of the moving range of the lioness, whose purpose is to dynamically update the search range to promote convergence, $p_i^k$is the historical optimal position of the i-th lion in the k-th generation, and gk is the historical optimal position of a hunting partner randomly selected in the k-th generation female lion group [17,18].

The young lion adjusts its position as follows:

$$x_i^k = \begin{cases} \dfrac{p_i^k + g^k}{2}(1 + \alpha_c \gamma), q \le 1/3 \\ \dfrac{p_m^k + p_i^k}{2}(1 + \alpha_c \gamma), 1/3 \le q \le 2/3 \\ \dfrac{g^{'k} + p_i^k}{2}(1 + \alpha_c \gamma), 2/3 \le q < 1 \end{cases} \tag{5}$$

where $p_m^k$is the cub following the liones. The best position in the history of the k-th generation; g'k is the position where the i-th lion cub is driven away within the hunting range. It is a typical elite reverse learning idea in a place far away from the lion king, and the probability factor q is according to a random value generated by the uniform distribution. And αc is the disturbance factor of the cub's moving range, defined as:

$$\begin{cases} \alpha_c = step \cdot ((T - t) / T) \\ step = 0.1(high^{'} - low^{'}) \end{cases} \tag{6}$$

where step represents the maximum step size of the lion moving within the range of activities, T is the maximum number of iterations of the lion group, and t is the current number of iterations; low' and high' are the minimum and maximum mean values of each dimension within the activity space of the lion, respectively [17].

However, the matrices ω and b of the BP neural network model often need to be manually derived from the input and output data to find the optimal values, which will consume a great deal of time and have high errors. Therefore, to optimize the parameter matrix ω and b, the LSO algorithm is used to optimize the BP neural network model to replaces the process of manually adjusting parameters. The optimal neural network weights and thresholds are finally obtained to improve the speed and accuracy of the prediction model.

3.2.3. Model Parameters Setting

The LSO algorithm optimizes the weight ω and threshold b of the BP model, and the parameters of the LSO-BP neural network model are shown in Table 2.

Table 2 LSO-BP model structure parameters and learning parameter settings.

Structural parameters	Value	Structural parameters	Value
Input layer neuron number	5	Epoch	5
Output layer neuron number	3	Batch Iteration	16
Hidden layer neuron number	20	Learning rate	0.0001
The dimensions of each lion	2	Maximum number of iterations of LSO	200
Number of lions	20	Adult lion ratio β	0.4

Rapid Estimation Method of VRLA Batteries capacity based on discharge voltage-LSO-BP

In this section, a rapid capacity estimation method of VRLA batteries based on the discharge voltage-LSO-BP is designed. As shown in Figure 4, the main steps of the proposed method are as follows:

1. Obtain characteristic parameters such as discharge voltage and discharge capacity of the VRLA battery samples during the 2h before the capacity test, and the detailed steps can be found in section 3.1.

2. Embedding the LSO algorithm in the BP neural network model to optimize the parameter matrix of the BP neural network model and to obtain the optimal network weights and thresholds. The optimization steps are described in detail in section 3.2 and will not be repeated here.

3. Based on the discharge voltage-LSO-BP model, a regression prediction model with five inputs and three outputs constructed, which can be described as follows:

$$\{a^*, b^*, c^*\} = f\,(U_p, U_t, a, b, c) \tag{7}$$

The input vectors are the fitted coefficients {a, b, c} for the discharge voltage and capacity of the VRLA battery over 2h, the peak voltage Up and the trough voltage Ut, respectively, and the output vectors are the fitted coefficients {a*, b*, c*} for the quadratic polynomial function. The determination of the fit coefficients means that the relationship between the discharge voltage and the capacity of the VRLA batteries has been determined. Therefore, when the discharge voltage is determined, the discharge capacity can be easily found.

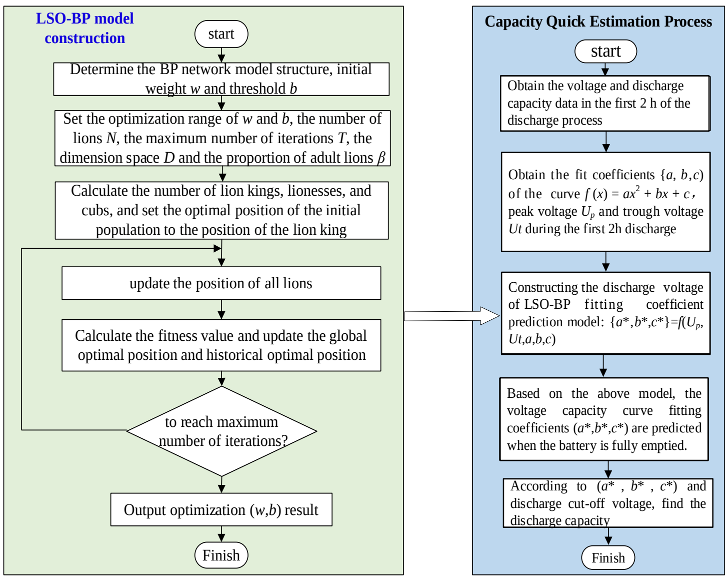


Figure 4. The framework of the rapid capacity estimation method of VRLA batteries based on discharge voltage-LSO-BP.

IV. Verification Results and Analysis

Figure 5 shows the time characteristics of discharge voltage and capacity in this test. It can be seen from Figure 1 that under different floating voltage conditions, the voltage of each sample appears steep drop and rise again at the beginning of discharge, that is voltage "Coup de Fouet", but its peak voltage and valley voltage are different. Moreover, when the peak voltage appears, the voltage decreases quasi-linearly, and when the discharge cut-off voltage is close to 1.8 V, it is significantly non-linear and the waveform is "tail" phenomenon. Furthermore, as the number of cycles increases, the peak voltage, valley voltage and capacity of the capacity-voltage curve in Figure 1 all change to varying degrees. Therefore, according to the phenomenon of "Coup de Fouet" in the early stage of VRLA batteries discharge and the correlation between discharge voltage and capacity, a rapid estimation method is designed in Section 3.

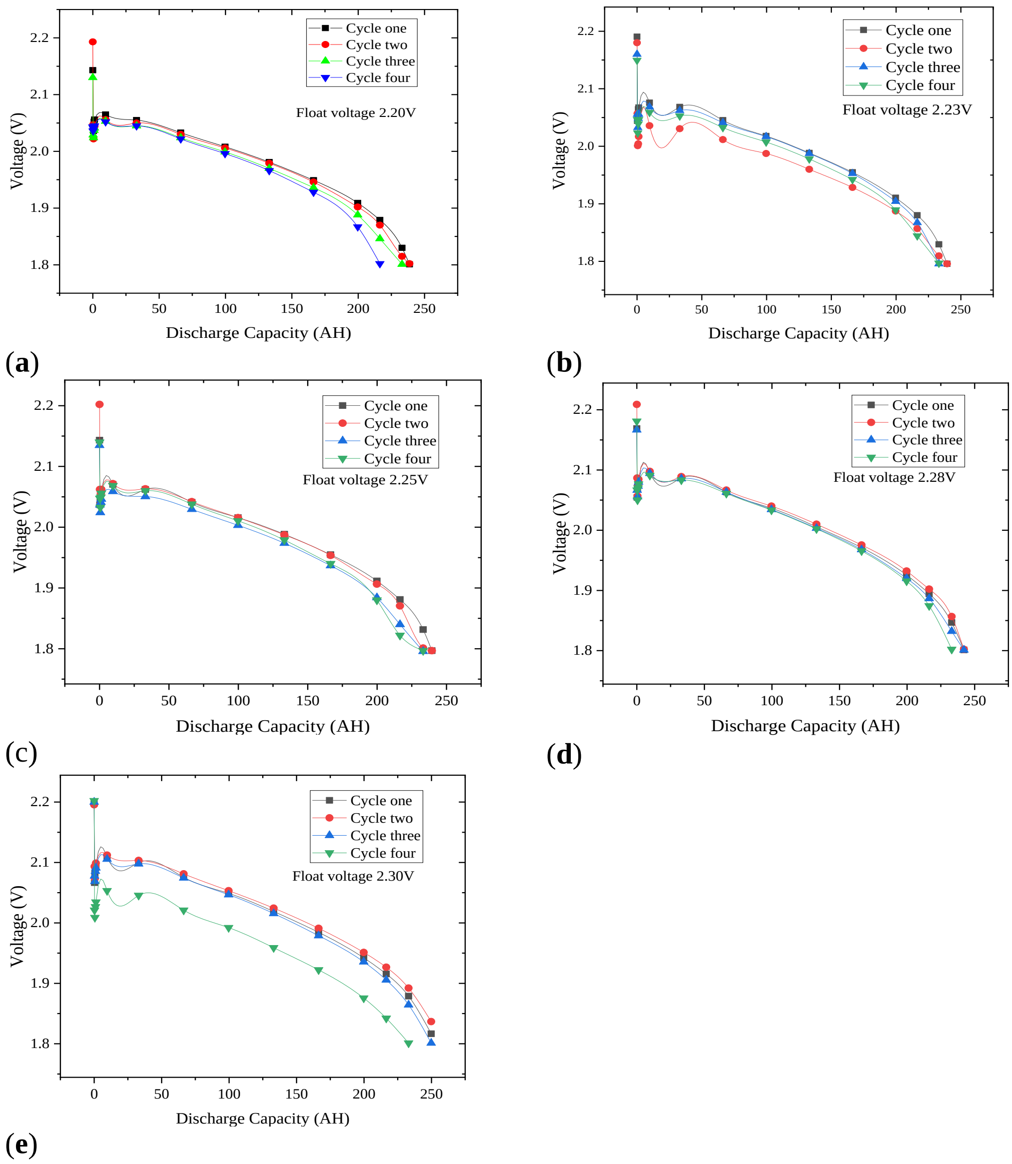


Figure 5. Voltage waveform of nuclear capacity process of 5 battery samples. (a) Floating charge voltage of 2.20V, (b) Floating charge voltage of 2.23V, (c) Floating charge voltage of 2.25V, (d) Floating charge voltage of 2.28V, (e) Floating charge voltage of 2.30V.

Five randomly VRLA batteries are selected. The floating charge voltage cut-off voltages of the five verification batteries are 2.20V, 2.23V, 2.25V, 2.28V and 2.30V, respectively. Using a leave-one-out evaluation method to validate the effectiveness and adaptability of the method. That is for each predicted capacity of a battery, the other four battery samples' data are used for training.

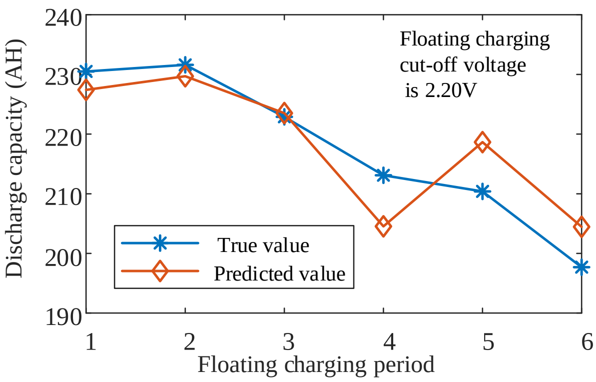
The results of the estimation of the discharge capacity of the VRLA battery under five floating charge operations are shown in Figure 6. As seen in Figure 6, there is a slight difference in the discharge capacity of the batteries for the five different floating charge cut-off voltages, with the higher floating charge cut-off voltage having a higher discharge capacity. The estimated discharge capacity of #1~#5 batteries fluctuate around the real value during the float charge cycle, and the average absolute error of the estimated discharge capacity of #1~#5 batteries is 3.492AH, 0.349AH, 1.23AH, 1.31AH, 5.438AH, and the maximum absolute error is 10.362AH, 8.564AH, 7.83AH, 9.42AH, 11.38 AH in turn.

To better illustrate the estimation accuracy, the algorithm is executed 30 times, and the model performance is evaluated by the average of the root mean square error (RMSE) and the maximum absolute percentage error (MAPE) of the 30 model estimation results. The statistical results are shown in Table 3.

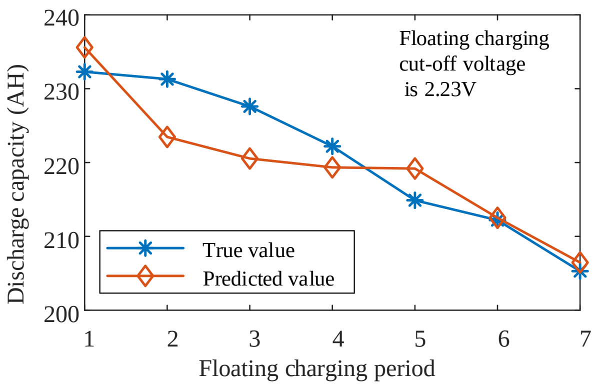
RMSE is the average value of the mean square error of the output results of the capacity prediction model, which reflects the degree of deviation between the output value of the capacity prediction model and the real value. The smaller value of RMSE the smaller the deviation of the output value of the capacity prediction model from the true value, and the higher the accuracy of the model. According to Table 3, it can be found that the RMSE value of the LSO-BP capacity estimation model is 1.70%, which is significantly lower than the 5.83% of the BP estimation model, and the estimation result is closer to the true value.

MAPE indicates the average absolute percentage error between the error of the capacity prediction model and the true value. According to Table 3, it can be found that the MAPE value of the LSO-BP capacity prediction model is 3.80%, which is also lower than that of the BP estimation model.

The capacity estimation model based on discharge voltage-LSO-BP proposed in this paper has good adaptability for batteries with different floating charge conditions and better estimation accuracy.



(a)



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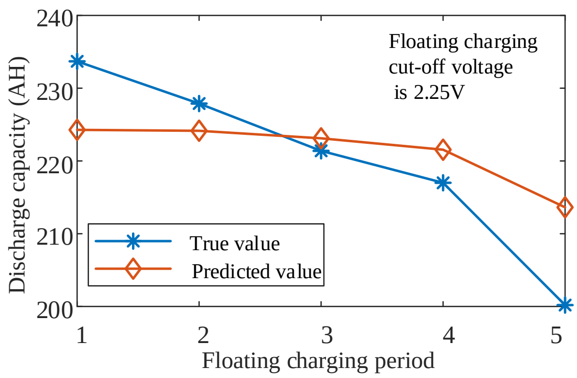

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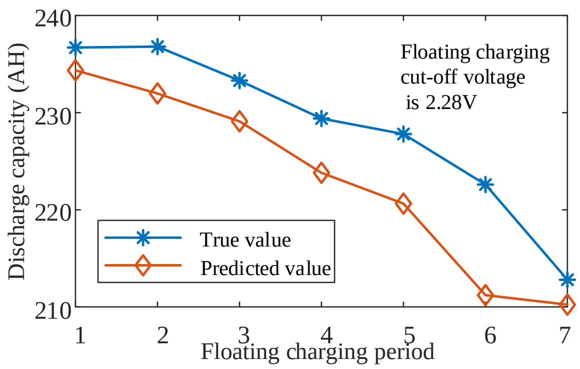

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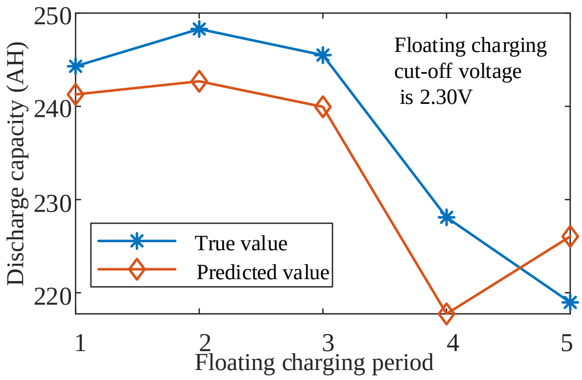

(e)

Figure 6. Estimation results of the capacity of 5 floating batteries. (a) Floating charge voltage of 2.20V, (b) Floating charge voltage of 2.23V, (c) Floating charge voltage of 2.25V, (d) Floating charge voltage of 2.28V, (e) Floating charge voltage of 2.30V.

Table 3. Calculation results of evaluation indicators of LSO-BP and BP.

Model	RMSE	MAPE
LSO-BP	1.70%	3.80%
BP	5.83%	4.76%

V. Conclusions

In this paper, a rapid capacity estimation method of VRLA batteries based on the discharge voltage-LSO-BP is designed. The suggested method's precision and speed are demonstrated through the testing of five VRLA samples with a floating charging pressure. The main conclusions are as follows:

1. Based on the phenomenon of "Coup de Fouet" in the early stage of discharge and the fitting relationship between the discharge voltage and the discharge capacity, the peak voltage, and the valley voltage during the first 2 hours of discharge, the fitting coefficient after complete emptying is predicted, and the discharge voltage and the fitting relationship of the discharge capacity was used to calculate the discharge capacity.
2. The simulation results show that the proposed method can significantly improve the accuracy of capacity estimation, significantly reduce the testing effort and reduce the depletion of VRLA batteries' lifetime by discharge testing, which provides a reference for rapid capacity prediction of other batteries in substations in the future.
3. The VRLA battery specimen used in the accelerated float durability test and the proposed life prediction method in this paper is DJ200, and its applicability to other brands and types of batteries is unknown. In the future, we will consider adding more brands and types of batteries as specimens to study the life prediction method with a wide range of applicability.

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