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Predictive Maintenance of VRLA Batteries in UPS towards Reliable Data Centers ⋆

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Abstract: The reliability of data centers can be severely affected when battery failure occurs in the Uninterruptible Power Supply (UPS). Thus it has become a central issue for the industry to discover failure-impending batteries in UPS. In this paper, we consider this important problem and present a data-driven method for predictive battery maintenance. The major contributions are as follows.*First*, we develop a changepoint detection technique for efficient data labeling. *Second*, new features are designed to fully utilize the dataset. *Third*, we build a predictive classification model which can discriminate between healthy and failure-impending batteries. Our method has been built and evaluated on 209,912,615 records from Tencent data center involving nearly 300 batteries monitored over 2 years. The experiment on test set shows that our method is able to predict battery replacement with 98% accuracy and averagely 15 days in advance, which outperforms the previous maintenance policy by more than 8%.

Keywords: Predictive maintenance, data-driven, classification, smart power applications

1. INTRODUCTION

With the rapid development of information technology and related industries, the Uninterruptible Power Supply (UPS) has become a reliable guarantee for the operation of Internet Data Centers (IDCs). UPS power solution (either AC-UPS or DC-UPS) can provide a backup, uninterrupted, constant power supply in the event of input power failure thus plays an important role in the sustainability and safety of the entire data center.

According to Scott et al. (2017), the Valve-Regulated Lead-Acid (VRLA) batteries are the most popular UPS battery type currently due to their energy density, rechargeability and economy. In most cases, the VRLA batteries are used in a series connection, once there exists a faulty battery, the performance and lifetime of the battery pack will deteriorate dramatically (An and Gao (2014)), which endangers not only the health of UPS but also the reliability of data center. Fortunately, most VRLA battery failures are predictable, which mainly result from slow processes that typically progress over months or years, such as grid corrosion and frozen positives (Barré et al. (2013)). This makes it possible to perform predictive battery maintenance using monitoring data.

However, there are some difficulties one may encounter when conducting this work. *First*, since batteries used in UPS are normally operated under conditions of floating charge, the monitoring data is much less informative than that collected in a lab. *Second*, there lacks industry standard for battery replacement, the maintenance depends mainly on expert knowledge. *Third*, battery failure is a rare occurrence, which means the data we obtained is highly unbalanced, making the task of finding high quality models challenging.

In this paper, we introduce a novel data-driven technique for predictive maintenance of VRLA batteries in UPS based on historic battery replacement data from an expert-maintained environment. First, We collect over 200 million records from 292 batteries monitored over 2 years from Tencent data center. The data points are labeled via a proposed changepoint detection method. Next, we expand data dimensionality by constructing new features to take full advantage of information contained in the dataset. Finally, we build a predictive classification model which can discriminate between healthy and failure-impending batteries. We show that our model is not only able to predict impending replacements weeks in advance, but can also detect potential battery failures that go beyond expert knowledge. This work has already been deployed in Tencent data center.

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The rest of this paper is organized as follows. We briefly review the related work in Section 2, describe the predictive pipeline in Section 3. Experiment analysis is presented in Section 4. Finally, Section 5 concludes the paper and introduces several future works.

2. LITERATURE REVIEW

Typically, there are two types of method for battey failure detection and maintenance.

One is manual inspection; that is, experts conduct on-site tests to infer the health status and remaining lifetime of batteries (Salameh et al. (2017)). *Discharge test* is the most direct and accurate way to detect battery capacity. However, it requires complicated measurement procedures, high technical requirements and disconnection of the batteries from DC system, which introduces risks to the UPS. *Conductivity test* inferring battery health by utilizing a dedicated portable conductivity measuring device. This method can only provide a rough evaluation of battery health for that conductivity is only one of numerous factors that may affect a battery's health.

Another type is online automatic detection, i.e., an automatic system, such as a battery testing instrument with some designed algorithm, is used to detect battery health. Methods include: (a) *Open-circuit voltage* (Snihir et al. (2006); Lee et al. (2008)), which is a relatively accurate indication of remaining capacity. But the battery must be detached from the system to measure open-circuit voltage, which is not allowed by most of UPS. (b) *Internal resistance*. Sato and Kawamura (2002); Zhao et al. (2010) proofed that there is a direct link between internal resistance and remaining lifetime for VRLA batteries. However, the internal resistance varies between battery batches and manufactures, making it challenging to formulate the method. (c) Some uncommon methods like *fuzzy control theory* (Wang and Suo (2013)), *wavelet transform algorithms* (Zhang et al. (2016)). These methods are not perfect enough in theory and hardly practical.

Among these monitoring methods, researches about the **state of health (SOH)** (Shahriari and Farrokhi (2013)) aim to find out how many times a battery can be charged and discharged while supplying the required power. Also, **remaining useful life (RUL)** prediction (Ren et al. (2018); Gregory W. Ratcliff (2019)) is another concern. Basically, most studies make use of cycle characteristics to estimate battery health as well as its remaining life.

Unlike the situation discussed above, batteries in UPS work much differently. Normally, UPS units are operated under condition of floating charge, the cycle characteristics cannot be obtained unless power supply fails which is a rare occurrence. To the best of our knowledge, very few studies have explored health evaluation and maintenance of batteries in UPS.

3. PREDICTIVE MAINTENANCE OF VRLA BATTERIES

3.1 Data Collection

We firstly collect 238,758,894 records from 292 batteries monitored over 30 months (June 2016 to December 2018) in Tencent data center (Tianjin), in which 32 batteries have been replaced. The data is collected with minute-level granularity containing the following: (1) timestamp, (2) serial number of battery, (3) serial number of battery pack and (4) basic battery attributes as presented in Table 1.

Attribute	Notation	Acquisition Frequency
Current	I_t	per minute
Voltage	V_t	per minute
Resistance	R_t	per week (the collected R_ts remain the same for one week)
Temperature	T_t	per minute

Table 1. Data acquisition information. The subscript denotes minute-level time t.

Next, we exclude records with missing attributes (accounts for about 8% of the raw data) or general knowledge errors (e.g., negative value of resistance). Then we restrict analysis to samples collected under condition of floating charge. Finally, we obtain a dataset consisting of 209,912,615 samples. Table 2 exhibits some statistics of the dataset.

	Voltage(V)	Resistance(mΩ)	Temperature($^\circ$C)
Mean	13.58	2.32	22.11
Std	0.17	0.81	1.34
Min	9.07	0.86	17.65
Max	16.61	33.12	30.12

Table 2. Some statistics of collected dataset.

3.2 Computer-aided Data Labeling

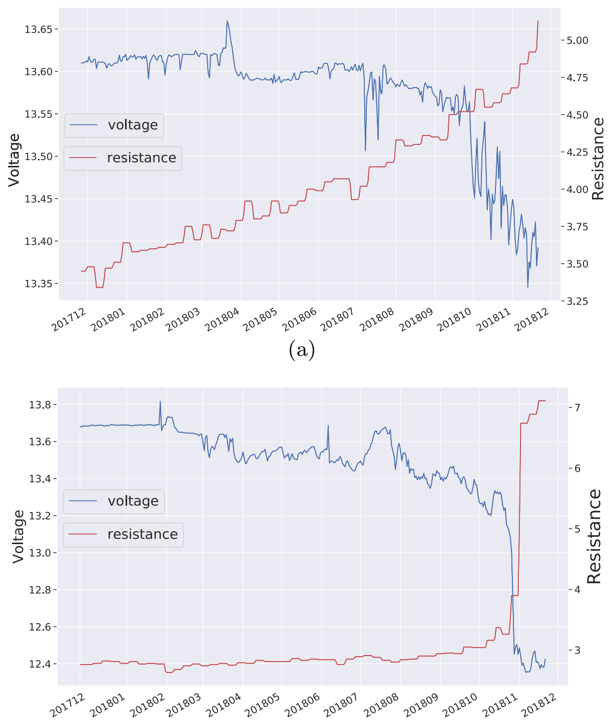
A battery is labeled as failed after an event that leads to replacement occurs, we call this event an Event of Interest (EoI). An EoI is usually one of the following type:

(1) *Natural Aging.* The ohmic resistance of VRLA battery smoothly increases with the aging of battery, causing battery capacity attenuation. According to industry-wide standard, a VRLA battery is suggested to be detached from system when its resistance reaches 5 mΩ.
(2) *Internal Fault.* An internal fault may lead to dramatic deterioration of battery health, which endangers not only the battery pack but also the safety of UPS.

Fig. 1 gives an example of natural aging and internal fault, respectively.

However, battery replacement only occurs during manual inspection every 4 months. In order to find the exact time of EoI, we have to check historical data manually. To eliminate repeated and heavy manual labor in this step, we develop an algorithm that automatically discover the time point when a battery begins to degenerate. We name this time point ***changepoint***. Following is a detailed description of the algorithm.

For the case of *Natural Aging*, as the resistance increases smoothly, we set the changepoint $t_c = t_f - 30 \times 24 \times 60$ minutes where t_f is the time when R_{t_f} reaches 5 mΩ. For the case of *Internal Fault*, the floating voltage of battery will decrease and fluctuate drastically in the early stage of



(a)

(b)

Fig. 1. Examples of events leading to battery replacement. (a) Natural Aging. The resistance reached 5 mΩ in the middle of November 2018. (b) Internal Fault. The fault occurred in early August 2018.

failure, which is indicative of a battery replacement. We firstly define an indicator of floating voltage decrease,

$$D_t = \sqrt{\sum_{i=1}^{W} w_i \cdot \min\{V_{t-i} - Median[V_{(t-2M):(t-M)}], 0\}^2}, \tag{1}$$

where $M, W \in \mathbb{Z}_+$ are time spans, $Median[V_{(t-2M):(t-M)}]$ is the median of $\{V_i | i = t-2M, t-2M+1, \cdots, t-M-1\}$, and $\{w_i | i = 1, \cdots, W\}$ are the weights satisfying $\sum_{i=1}^{W} w_i = 1$. In our case M is set to be $30 \times 24 \times 60$ minutes and W is set to be $7 \times 24 \times 60$ minutes. Then the changepoint t_c is defined as

$$t_c = \min_t \{t | D_t \geq 3\sigma_e\}, \tag{2}$$

where σ_e is the mean of the empirical standard deviations of the floating voltage of all samples labeled as healthy. Fig. 2 illustrates how this algorithm works in the latter case.

Since changepoint indicates when a significant change of battery performance occurs, we are able to narrow down the hunting zone of EoI to several days around changepoint, bringing significant time saving and efficiency promotion in data labeling. After this step, we obtain 209,465,400 healthy samples and 447,215 failed samples.

3.3 Feature Design

The collected dataset is in large amount but low dimensionality. To fully utilize the power of big data, we expand the data dimension by some feature design methods.

1) *Basic Features.* The data collected from battery monitoring device contains some basic attributes: current, voltage, ohmic resistance and temperature. Considering that the floating current is always zero regardless of the battery's health, we employ the latter three attributes as our basic features, namely V_t, R_t, T_t.
2) *Battery Pack Related Features.* Batteries in UPS are used in a series connection, with each serial battery pack consisting of a fixed number of individual battery cells. As the performance of battery pack is seriously affected by faulty cells, intuitively we expect that battery pack attributes can reveal potential failure of cells it contains.

   Therefore, we design some features representing battery pack statistics, such as the mean and empirical standard deviation of voltage of battery cells μ_t^V, σ_t^V, the mean and empirical standard deviation of ohmic resistance of battery units μ_t^R, σ_t^R. Formally,

$$\mu_t^V = \frac{1}{N} \sum_{i=1}^{N} V_t^{(i)}, \tag{3}$$

$$\sigma_t^V = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (V_t^{(i)} - \mu_t^V)}, \tag{4}$$

   where N represents the number of battery units contained in a battery pack and $V_t^{(i)}$ is the voltage of battery cell $i, i \in \{1, \ldots, N\}$ at time instant t. μ_t^R and σ_t^R are formulated in the same way.

   Furthermore, the relative performance to the intra-pack average could be highly informative for inferring a battery cell's health. Thus we employ two indicators named *relative voltage* RV_t and *relative resistance* RR_t to our predicting model. They are given as

$$RV_t = V_t - \mu_t^V, \tag{5}$$

$$RR_t = R_t - \mu_t^R. \tag{6}$$

3) *Time Series Features.* The monitoring data are gathered over time. There are several observations that hint the necessity of constructing time series features: (i) Some attributes show high time dependency. (ii) The model will not be able to predict replacement if we consider only attributes from the last minute of the battery before replacement as observations for the failed class.

   Therefore, we calculate both the rate of change and the gradient of some attributes for consecutive days. Formally, the voltage change rate at time instance t is defined as

$$VC_t = V_t - Mean[V_{(t-T_c):(t-T_c+D)}], \tag{7}$$

   where T_c is the time period used to calculate the change rate, D is the number of time instances contained in one day.

   The voltage gradient at time instance t, denoted by VG_t, is obtained by solving the following least squares regression problem:

$$\min_{a_0, a_1} \sum_{i=t-T_g}^{t} ||V_i - (a_0 + a_1 \cdot i)||^2, \tag{8}$$

   where T_g is the time period used to calculate the gradient. We assign $VG_t = a_1$ after an optimal solution is achieved. The resistance change rate RC_t and the resistance gradient RG_t are defined similarly.

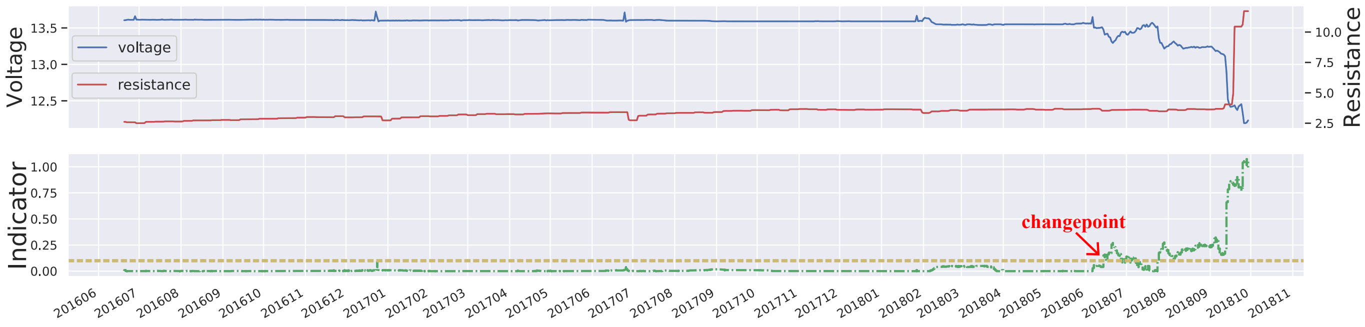


Fig. 2. Changepoint detection in the case of internal fault. The upper figure shows basic attributes V_t, R_t of the battery throughout its life cycle. The lower figure demonstrates the corresponding indicator D_t, the yellow dash line refers to the threshold $3\sigma_e$, which is set to be 0.099 in our case.

4) *Combined Features.* In order to introduce nonlinearity into our model, feature combination approach is adopted to create a new feature $VDR_t = V_t/R_t$.

Finally we expand the feature space to 14 dimensions.

Type	**Feature Name**	**Notation**
Basic Feature	Voltage	V_t
	Resistance	R_t
	Temperature	T_t
Battery Pack Related Feature	Pack Voltage Mean	μ_t^V
	Pack Voltage Std	σ_t^V
	Relative Voltage	RV_t
	Pack Resistance Mean	μ_t^R
	Pack Resistance Std	σ_t^R
	Relative Resistance	RR_t
Time Series Feature	Voltage Change Rate	VC_t
	Voltage Gradient	VG_t
	Resistance Change Rate	RC_t
	Resistance Gradient	RG_t
Combined Feature	Attribute Ratio	VDR_t

Table 3. Summary of Features.

3.4 Class Balancing

As battery replacement is a rare occurrence, the data to be used for training predictive model is highly imbalanced. In our case, the ratio of healthy and failed samples is nearly 468:1. However, most classification algorithms minimize the overall errors, the trained model will exhibit poor performance when fed with our imbalanced data. To tackle this problem, we undersample the healthy class using the approach described in Botezatu et al. (2016). The key idea is to cluster the healthy samples into k clusters, then select n data points nearest to the respective cluster centroid for each cluster as representatives. In our case, k is chosen to be 50 and n is 10,000. Finally we obtain a balanced dataset for the next step.

3.5 Model Training and Online Deployment

We train a classification model for battery replacement offline using the dataset generated in the previous step. We expect the model to deliver high quality prediction on both training data and unseen testing data. Formally, let $D = \{(\boldsymbol{x_i}, y_i)\}_{i=1}^N$ denote the train set, where $\boldsymbol{x_i} \in X$ is the 14-dimensional variable containing battery information during time instant $t_{i-\max\{T_c,T_g\}}$ to t_i. $y_i \in \{0,1\}$ is a binary variable indicating whether the battery represented by $\boldsymbol{x_i}$ needs replacement. Our goal is to learn a function: $f : X \to \{0,1\}$ that minimizes the loss $\sum_{i=1}^N L(f(x_i), y_i)$, which quantifies the prediction accuracy.

We conducted comparative experiments of Random Forests (Breiman (2001)), Gradient Boosting Decision Tree (Friedman (2001)), Artificial Neural Network (Sarle (1994)) and Logistic Regression (Cox (1958)) models for our classification task, and finally choose *Gradient Boosting Decision Tree* (GBDT) for online deployment due to its accuracy, efficiency and ease of implementation. The balanced dataset obtained in last step is used as train set, parameter tuning and 3-folds cross validation are applied to achieve better performance. The learning rate is set to be 0.05 and the number of boosting stages is set to be 300.

Figure 3 shows the online deployment schema of our predictive battery maintenance method. Once our model find a latent failed battery, expert will conduct on-site examination. If the classification outcome is TP, i.e. the battery do has impending failure, a replacement request will be submitted to the control center. Otherwise, the instance will be stored for future training.

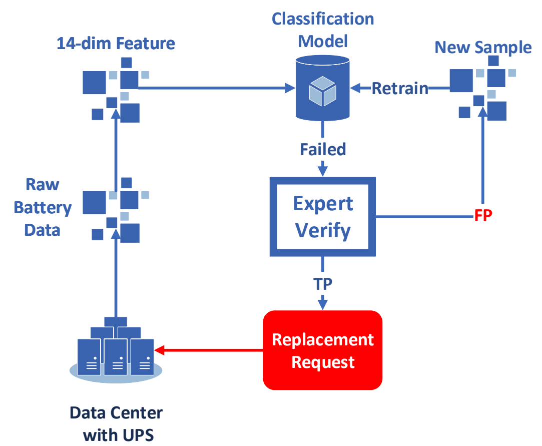


Fig. 3. Online deployment Schema.

4. EXPERIMENTAL ANALYSIS

In this section, we present our experimental results and show the superiority of our proposed method. To evaluate the performance of classifiers (maintenance polices), we measure precision, recall, and F-score as defined below.

$$P = \frac{tp}{tp + fp}, \quad R = \frac{tp}{tp + fn}, \quad F = \frac{2}{P^{-1} + R^{-1}}.$$

4.1 Comparison with Expert-Designed Policy

Previously, UPS batteries in Tencent data centers were maintained under an expert-designed policy. The policy consists of 6 simple rules based on battery attributes collected by monitoring devices. For example, if $R_t > 5m\Omega$, the policy gives an outcome of *Replace*.

We collect over 20,000,000 new battery samples from Tencent data center as *test set*. Both expert-designed policy and our proposed policy are performed on the test set. The results demonstrate that our method brings significant improvement in identifying failure-impending batteries over the previous maintenance policy. Please refer to Table 4 for details.

		Expert-Designed Policy	**Proposed Policy**
Replaced	Precision	0.981	0.962
	Recall	0.687	**0.999**
	F-score	0.808	**0.981**
Healthy	Precision	0.818	**0.987**
	Recall	0.990	0.972
	F-score	0.896	**0.979**

Table 4. Precision, Recall, F-score of two maintenance policies on test set

Furthermore, our policy is able to detect an impending failure ***fifteen days*** in advance on average, allowing administrators to plan properly for replacements. Figure 4 gives an example of replacement prediction.

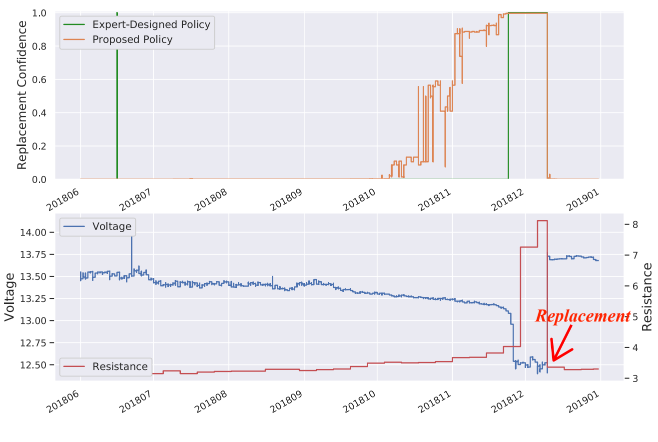


Fig. 4. Example of replacement prediction. The lower figure shows basic attributes V_t, R_t of the battery. The upper figure shows the replacement confidence correspondingly given by two maintenance polices.

As shown in the lower subgraph, the battery deteriorated dramatically in late November and was replaced in December. Expert-designed policy predicts the replacement two weeks in advance, few days before the deterioration. Our proposed policy identifies the impending replacement nearly a month ahead of expert-designed policy and hence shows a major advantage.

4.2 Benefits of Feature Expansion

We employed feature expansion technique in Section 3.3 to capture as many patterns as possible and hence obtained an intelligent predicting model. To illustrate the benefits of feature expansion, we calculate importance of each feature within model. According to Breiman (2017)'s work, importance of feature j in a boosted tree model is given by:

$$\hat{J}_j^2 = \frac{1}{M} \sum_{m=1}^{M} \hat{J}_j^2(T_m), \tag{9}$$

where M is the total number of trees, $\hat{J}_j^2(T_m)$ is importance of feature j in a single decision tree T_m, which is defined as:

$$\hat{J}_j^2(T_m) = \sum_{t=1}^{L-1} \hat{I}_t^2 \mathbf{1}(v_t = j), \tag{10}$$

where L is the number of terminal nodes, v_t represents the splitting attribute associated with node t, and $\hat{I}_t^2$ is the corresponding improvement in Gini index resulted from the splitting.

We present the six most important features in Figure 5. The result reveals that only one of them (Voltage) is collected directly from monitoring device, which indicates the benefits of feature expansion.

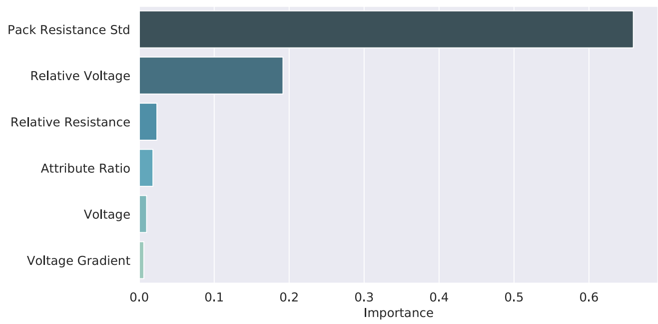


Fig. 5. The six most important features in construction of our predicting model.

Also, we trained the model by applying aforementioned feature design techniques step by step, and present F-scores for replaced class in the following.

As shown in Figure 6, we receive a F-score of 0.678 when utilize only basic features. By adding battery pack related features, the F-score increases to 0.889. Then it is improved by time series features to 0.925 and finally reaches 0.981 when combined features are taken into account. The results demonstrate the significance of feature design process.

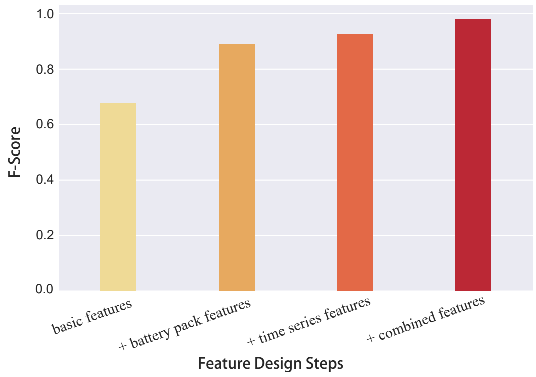


Fig. 6. Improvements in F-score by adding features step by step.

5. CONCLUSION

In this paper, we present a data-driven approach for predictive maintenance of VRLA batteries in UPS based on historic battery replacement data and GBDT model. We have collected nearly 200 million training samples from batteries in Tencent data center and developed a changepoint detection method for efficient data labeling. Moreover, we have applied feature expansion technique to fully leverage the power of big data. Eventually, the experiment results show that our approach outperforms the current maintenance policy by more than 8%. This work have many practical benefits. First, the model works automatically and no extra effort is necessary. Second, the model can be easily implemented on VRLA batteries from any manufacture as long as basic battery attributes are collected. This work has been deployed in Tencent data center (Tianjin) and performs well so far.

In the future, it is interested to generalize our model to predict replacement of batteries from different manufacture, as well as predict other facility replacement in data center.

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