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Consistency Analysis of Large-scale Energy Storage Batteries

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Abstract. With the development of large-scale electrochemical energy storage power stations, lithium-ion batteries have unique advantages in terms of re-energy density, power density, and cycle life, and are applied to power system energy storage devices. However, behind the rapid development, there are many key issues unanswered, which are likely to lead to various safety accidents. Therefore, it is very important to conduct consistency analysis of lithium batteries used in large-scale power systems to prepare for system safety assessment. This paper mainly explains the reasons and manifestations of the inconsistency, and based on data mining algorithms, uses the charging voltage curve clustering analysis method based on subtractive clustering to evaluate the consistency of lithium-ion batteries.

Keywords: Large-scale energy storage, data mining, consistency analysis, cluster analysis

1. Introduction

Lithium-ion batteries are widely used in electric vehicles, electric energy storage and other fields due to their excellent performance in energy density, volume density, output voltage, cycle life and other parameters[1-2]. In practical applications, the voltage or capacity of a single lithium-ion battery is insufficient to meet the system's requirements for indicators such as capacity, power, and output voltage. Therefore, it is often necessary to connect single batteries in series and parallel to form a battery pack. With the development of large-scale electrochemical energy storage power stations, the power system will have higher and higher requirements for the consistency of energy storage batteries.

However, due to the different manufacturing processes and use environments of the single cells [3], lithium-ion batteries for power storage must have large or small inconsistencies, which will greatly reduce the performance of the battery pack. When the inconsistency increases , It can be suspected that there are faulty battery cells or faulty battery modules in large-scale energy storage power stations, which greatly affects the safe operation of energy storage power stations. In severe cases, fires, explosions and other accidents may occur. Therefore, real-time safety status analysis of battery cells is important for large-scale The safe operation of large-scale energy storage power stations is essential. Therefore, the consistency analysis of lithium-ion batteries is of great significance for improving their use efficiency, operating performance and safety. Currently, the consistency evaluation of lithium-ion batteries has become a hot research topic in the fields of electrochemistry, test and measurement, and reliability.

2. Causes and manifestations of inconsistency

The inconsistency of lithium-ion batteries refers to the inconsistency of the parameters of each single lithium-ion battery. Usually, the inconsistency of a new batch of lithium-ion batteries is very small. The inconsistency will gradually increase. It is difficult for the single lithium ion battery to meet the high capacity and high efficiency requirements of the energy storage system. It is necessary to form hundreds of single lithium ion batteries into a battery pack as the energy storage power source.

The inconsistency between the single lithium-ion batteries will have a great impact on the life of the battery pack, and even make the life of the battery pack less than the lithium-ion battery that composes the battery pack with the worst performance. Therefore, the consistency of lithium-ion batteries is of great significance to the grouping of battery packs; for grouped battery packs, timely detection and discovery of the inconsistency of lithium-ion batteries can prolong the service life of the battery pack and improve the performance of the battery pack, and the effect is very good.

2.1 Causes of inconsistency.

The inconsistency between battery cells can be divided into two categories. One is the inconsistency caused by the battery cells during the manufacturing process, which is also called a one-time inconsistency. The main reason

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is that the same batch of raw materials or the difference between different batches. The non-uniform nature of the space, the production of the electrode plate, the uniformity of the electrode layer, the amount of active material, the distribution of the particle size of the active material, the total amount of electrolyte and the degree of permeability, etc. The inconsistency of the battery once is the source of a series of problems in the subsequent battery system performance.

The second is that in the long-term operation of the single cell or battery pack, there are differences in some parameters between the single cells obtained due to the continuous cycle of charging and discharging, and the difference in the parameters increases the capacity of some single cells. The accelerated decay of the battery, which increases the inconsistency between the single cells, causes the performance difference between the single cells to enlarge, and seriously affects the cycle life of the battery pack. Among them, in the cycle of charging and discharging, the parameters between the single cells are changed, so that there are differences between the single cells, which are mainly caused by factors such as temperature and depth of discharge [4-5].

2.2 Manifestations of inconsistency.

The inconsistency of the battery mainly manifests in three aspects, namely the inconsistency of the capacity, the inconsistency of the internal resistance and the inconsistency of the voltage. The inconsistency of capacity refers to the different capacity of the battery, which will lead to inconsistent discharge depth of the battery, overdischarge of the battery with small capacity, and difference in the optimal discharge current. This is mainly because a battery with a small capacity will be completed ahead of schedule whether it is in the process of discharging or discharging. As other batteries continue to be charged or discharged, the battery with a small capacity continues to be charged or discharged, so that it is in an overcharge or overdischarge state[6-7]. The battery pack is formed by the series-parallel hybrid connection of single cells. The inconsistency of internal resistance can make the voltages allocated to the single cells in the process of discharging different, which leads to the overdischarge of some batteries with large internal resistance, but the internal resistance is small. The battery cannot be fully charged. The inconsistency of voltage is mainly manifested in the discharge of high-voltage battery cells to low-voltage battery cells in the battery pack, which is mainly for parallel battery packs. This will result in a sharp drop in the capacity of the high-voltage battery, which greatly affects the efficiency of the battery pack.

3. Clustering consistency evaluation method of charging voltage curve based on subtractive clustering

At present, the application of inconsistency is mainly through clustering between multiple single cells. Even if the consistency between batteries is analyzed, it is often to set a threshold for the difference between capacity, resistance, etc., with the threshold as the limit. The batteries above the threshold are inconsistent, and the batteries below the threshold are the same. The analysis and application of the degree of inconsistency are very few, and the definition of inconsistency is even rarer. In the actual analysis of lithium-ion battery sorting problems, the definition of the degree of inconsistency is of great significance to the solution of the problem. Zhang Bin put forward a concept of "dispersion" to characterize the inconsistency between single cells[8].

Cluster analysis is based on similarity and is an unsupervised classification, which has a wide range of uses in data mining and pattern classification. The cluster analysis method includes two aspects, one is the design of similarity in the cluster analysis, and the other is the selection of the clustering algorithm.

3.1 Lithium-ion battery charging curve similarity.

As the number of charging and discharging of lithium-ion batteries continues to increase, the internal resistance, electrochemistry and other polarization phenomena of lithium-ion batteries have led to changes in battery parameters. The charging voltage curve of a lithium-ion battery is a time series, which can express the changes in the internal parameters of the lithium-ion battery to a certain extent, and can be used as a basis for estimating and judging the consistency of the lithium-ion battery.

The similarity is usually obtained by further calculation of the distances in various multi-dimensional spaces, such as Ming's distance, Ran's distance, Mahalanobis distance, etc. Similarity generally appears in various methods in data mining, such as gray correlation degree in gray mathematics, etc. It is an important content of sequence data mining. Through literature data query, the commonly used similarity types are Ming's distance similarity, sequence similarity, gray correlation, and dynamic time warping distance similarity. In practical applications, the performance of lithium-ion batteries is not too different to a certain extent, and it is difficult to accurately classify the similarity based on the Minnian distance. In the process of voltage output, the output of the battery is a process of dynamic change due to electrochemical reaction and other reasons. Ming's distance, gray correlation degree, sequence similarity, etc. are all based on static distance, and it is difficult to show the curve change law of lithium-ion battery voltage curve due to load and other reasons. According to the output characteristics of lithium-ion voltage, this paper uses the idea of dynamic time warping similarity to design the voltage curve of lithium-ion battery.

Time series has various deformation, such as translation, expansion and contraction. Dynamic time warping similarity is proposed to solve the problem that Euclidean distance similarity is sensitive to the deformation of time axis of time series. Different from Ming's distance, which is calculated by static method, dynamic time curvature distance is calculated by dynamic programming. This will make the dynamic time warping distance more suitable for dynamic analysis and have better robustness. Dynamic time curvature line is not one-to-one alignment of each dimension data of two sequences that need similarity calculation, but can be misaligned, and the misalignment alignment mode with the highest similarity can be obtained for dynamic processing, which can well adapt to the problems of time expansion, bending and linear drift. When the similarity degree of dynamic time warping is used in practice, the two sequences used for similarity calculation often have different dimensions. Let the dimensions of sequence and sequence be m and n respectively, and the dynamic time warping distance between sequence and different points of sequence be:

$$D\big(x_1(i), x_2(j)\big) = f(i,j) \tag{1}$$

$f(m,n)$ obtained from the formula:

$$f(i,j) = |x_1(i) - x_2(j)| + min\begin{cases} f(i,j-1) \\ f(i-1,j) \\ f(i-1,j-1) \end{cases} \tag{2}$$

Where $f(0,0) = 0$, $f(i,0) = 0$, $f(0,j) = \infty$, that is, continuous recursion, can be obtained an $m \times n$ dimensional dynamic time warping distance matrix is the dynamic time warping distance between different points of the matrix sequence x_1 and sequence x_2. The dynamic time warping distance between sequences is to find the best alignment by finding the best path. The dynamic time bending distance usually uses the Euclidean distance, and the best path found in the matrix reflects the minimum sum of the Euclidean distance of the points on the path. Among them, when searching for the best path, several conditions need to be met, namely the boundary, continuity and monotonicity of the road. Boundary refers to starting from coordinates (1,1) and ending at coordinates (m, n), and the path is believed to be continuous between the two points, and the path is also proceeding in the direction of monotonous connection. By calculating the distance between similar points, the accumulation of the distance between each similarity is used as the sequence and the sequence's dynamic time warping distance $D(x_1, x_2)$:

$$D(x_1, x_2) = \sum_{i,j} f(i,j) \tag{3}$$

Where (i, j) is the path coordinates included in the obtained optimal bending path.

Assuming the dynamic time warping distance of the sequence and the sequence, the curve similarity of the sequence and the sequence based on the dynamic time warping distance is as follows:

$$sim(x_1, x_2) = 1/\big(1 + D(x_1, x_2)\big) \tag{4}$$

The charge and discharge data of Li-ion battery is not only the interference and error during collection, but also the internal interference affects the voltage change during the whole discharge process. The actual change of battery voltage caused by interference at a certain time will inevitably affect the change of battery voltage at the next time, and the application of dynamic time warping distance can reduce the influence of the change of charging voltage curve caused by this influence on similarity calculation.

3.2 Clustering based on subtraction.

Subtractive clustering is a density clustering method, in which the main idea is to divide all data points into one type, and then reduce the number of categories through continuous processing until the clustering meets the requirements. Compared with K-means method and K-medoids method, this method is no longer based on the distance between two clustered data, but on the density of each type, that is, the relationship between each data and all other data, and the classified categories are also exclusive.

Classical subtractive clustering is a circular process until the clustering meets the set requirements. There are two main steps in clustering. The first step is to calculate the density of the i-th data point, that is, the relationship between other data points and this data point. The density is obtained by the following formula:

$$M(v_i) = \sum_{k=1}^{n} e^{-\alpha d(x_k, v_i)} \tag{5}$$

Among them, the static distance between two data, which is usually defined as Euclidean distance, is the key to calculate the density. In this paper, the similarity between Li-ion battery charge-discharge curves is used as the basis for clustering, which is defined as the similarity between two Li-ion battery charge-discharge curves, and the dynamic time bending distance between the curves set above is selected. It is a parameter for calculating the density of each data point, which is usually obtained by formula.

$$\alpha = 4/\tau_1^2 \tag{6}$$

It is a constant that is often set according to actual processing problems or people. The larger its value, that is, the smaller its value, the smaller the data range that affects the density of this data point. The data points with the highest density are obtained as the first clustering center. The second step is to calculate other cluster centers in a circular way. Firstly, the cluster centers obtained in the previous step are removed, and the density index of the points is calculated.

$$M_k(V_i) = M_{k-1}(V_i) - M_{k-1}^* e^{-\beta d(V_{k-1}^* V_i)} \tag{7}$$

Where the previous cluster center is the density of the previous cluster center point, which is a parameter and is obtained by the following formula:

$$\beta = 4/\tau_2^2 \tag{8}$$

The value is a set parameter, which is used to simulate the influence of weight and can be used to solve the problem of coincidence clustering, and its value is usually greater than. There are usually two ways to end subtractive clustering. One is to set a number of types artificially, and when the number of cluster centers of subtractive clustering reaches this number, the loop ends. The other is to set a constant between 0 and 1 and calculate it by the following formula:

$$\frac{M_{k-1}^*}{M_k^*} < \delta \tag{9}$$

When the above formula holds, the loop is ended and all cluster centers are obtained. Then, according to the distance between the cluster center and other points, the types of other data points are obtained.

Curve similarity is based on the dynamic bending distance between sequences set above, that is, the similarity is the reciprocal of the dynamic bending distance. Based on the similarity obtained, the charging voltage curves of Li-ion batteries are clustered by subtractive clustering method, and the battery cells of large-scale energy storage power stations are classified..

4. Summary

This paper analyzes the causes and manifestations of inconsistency of lithium ion batteries. A density-based clustering algorithm is proposed to evaluate the battery inconsistency, which can solve the problem of battery inconsistency evaluation under the conditions of low volatility and non-equal dimension space. Based on the similarity of Li-ion battery curves obtained, the charging voltage curve clustering based on subtractive clustering is used to output the clustering results to analyze the consistency among batteries, which is a guide for finding and distinguishing battery packs in different states in energy storage power stations. After the effective identification of the battery system in the fault battery, for the battery system to develop an efficient safety management mechanism to provide a way.

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