A Hybrid Multiscale Permutation Entropy-Based Fault Diagnosis and Inconsistency Evaluation Approach for Lithium Battery of E-Vehicles

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ABSTRACT
Lithium battery is a complex nonlinear time-varying system with several inconsistencies. The fault diagnosis method has difficulty making an early diagnosis of battery faults without obvious abnormalities. In fact, voltage inconsistency is a representative fault response. Therefore, the monitoring of voltage inconsistency is highly important for the safe and reliable operation of lithium batteries in E-vehicles. The entropy method does not rely on an accurate analysis model and expert experience. Moreover, it does not consider the complex fault mechanism and system structure. Hence, it has gradually attracted widespread attention. Given such attention, a hybrid fault diagnosis method combining multiscale permutation entropy (MPE) and coefficient of variation (CV) is presented in this paper, and the improved MPE fault diagnosis model based on 3-sigma is emphasized. First, MPE and the 3-sigma rule are used to calculate the threshold, and the voltage inconsistency of the battery is judged by the threshold. Then, the location of the faulty cells is located by the CV. The superiority of the proposed method is proven by experimental data from the Yunzhitong platform of CRRC Electric Vehicle Co., Ltd. and a comparison of frontier methods. The proposed approach is feasible and promising in real E-vehicle applications.

INDEX TERMS
Electric vehicles, lithium battery, multi-scale permutation entropy (MPE), coefficient of variation (CV) rule, 3-sigma rule.

I. INTRODUCTION
In the desire to build a low or zero carbon-emitting society, compared with fossil fuels such as oil, gas, and coal, lithium batteries have the advantages of high energy density, high efficiency, high open-circuit voltage, long life, low self-discharge rate, and less pollution. Meanwhile, government subsidies for lithium batteries in recent years have brought down the cost of E-vehicles for consumers. As a result, lithium batteries have become the primary or auxiliary power devices of choice for E-vehicles, hybrid electric vehicles, and plug-in hybrid electric vehicles [1], [2]. Lithium battery, as the main energy storage device for E-vehicles applications, has a safety management feature that has attracted the attention of users and scholars [3], [4]. In recent years, a lot of skepticism has been raised about E-vehicles’ safety due to injuries and property damage caused by lithium-ion battery failures. Therefore, the acceleration of lithium battery fault diagnosis has a vital impact on the safety of E-vehicles [5], [6]. In fact, given the similar heat dissipation conditions, the temperature variation between cells is not evident. As all lithium batteries in the same cluster operate under the same conditions (such as frequency regulation), we can infer that the state parameters of a battery group, such as voltage should show similar change trends. In other words, when fault exists, the difference between voltage of each cell is obvious. Therefore, this paper contributes towards lithium batteries safety management by proposing a fault diagnosis model considering voltage inconsistency.

Lithium battery fault diagnosis is a multi-dimensional issue involving materials, manufacturing process, electricity, and thermodynamics, which bring forth the multidimensional complexity of E-vehicle applications and higher challenges to battery safety. According to the principle of
existing lithium battery fault diagnosis methods, they can be divided into model-based methods and non-model-based methods. Model-based diagnosis methods, such as the electrochemical model, mainly analyze the internal structure and components of battery through physical or chemical means [7], [8], such as electropuncture and electrolyte analysis. Model-based methods have a good effect on system diagnosis, but non model methods have always been the focus of research. Non-model-based diagnosis methods detect the state of batteries and generate data, such as temperature, voltage, and current. This information is then combined with intelligent algorithms in the model. The non-model-based method focuses on the establishment of a diagnosis rule based on a large amount of data through artificial intelligence algorithm [9]. The monitoring of battery states is of critical importance for guaranteeing the safe and reliable operation of E-vehicles [10], [11], [12]. Zhao et al. [13] proposed a novel method that combines machine learning algorithm and the 3-sigma strategy; the abnormal voltage changes of cells in a battery pack can be detected and calculated in the form of probability. Cai et al. [14] proposed the square root cubature Kalman filter (SRCKF) algorithm, which has been developed to estimate the SOC of batteries. Banguero et al. [15] designed the use of principal component analysis (PCA) for the state of health (SOH) diagnosis of a battery energy storage system (BESS). Wang et al. [16] and Shang et al. [17] proposed an in-situ voltage fault diagnosis method based on the entropy, which is capable of predicting the voltage fault in time through monitoring battery voltage during vehicular operations. How et al. [18] adopted the multi-model probabilistic battery state estimation method for electric vehicles. Li et al. [19] and Yao et al. [20] proposed an intelligent fault diagnosis method for batteries based on a support vector machine, which can identify the fault state and degree promptly and effectively. Tagade et al. [21] applied a deep Gaussian process algorithm for lithium-ion battery health monitoring. Cai et al. [22] presented an artificial intelligence enhanced model reliability by combining Bayesian neural networks (BNNs) and differential evolution (DE) algorithms, which proved that artificial intelligence can effectively improve the performance of the model. Kong et al. proposed a sensor placement methodology of a hydraulic control system to determine the optimal number and position of sensors based on a discrete particle swarm algorithm [23]. Cai et al. [24] designed a multistage fault prognosis methodology combining stage identification with Bayesian networks (BNs) and time series approach. These approaches all demonstrate the superiority of non-model-based diagnosis methods in the field of battery diagnosis.

Due to manufacturing, design [25], or assembly problems, a larger number of batteries entail larger capacity. A system with a larger number of batteries is more likely to have internal resistance of each cell and inconsistent parameters, such as voltage and current. A large inconsistency between batteries is considered the main factor leading to faults and even safety accidents. Voltage inconsistencies of cells is one of the common types of failure in battery systems, which are closely related to many interactive factors [26], [27]. Voltage failure reflects serious internal failure of E-vehicles, including mechanical fatigue, separator failure, and internal short circuit [28]. Gokmen et al. [29] designed a novel method based on wavelet-neural network (WNN) utilizing the actual voltage value for the lithium-ion battery pack in series online. Jiang et al. [30] proposed a novel data-driven method for lithium-ion battery pack fault diagnosis and normalized battery voltages, which are used to achieve the accurate identification of battery early faults. However, these approaches lack the ability to detect and locate the position of faulty cells, nor can it detect potential abnormal changes without obvious faults. One of the most effective methods [31] is to set a threshold. If the target output or its rate of change exceeds the threshold, it will be considered a failure. Ref. [12] is the first study to bring the 3-sigma rule to lithium battery diagnosis and its works by directly using the mean and mean standard error to set the upper and lower thresholds by 3-sigma, using real-time monitoring of individual parameters determines whether their values are within the permissible range. The 3-sigma rule method is a frontier approach to detect potentially abnormal changes in cell voltage to compensate for these defects. It utilizes an iterative loop to find the optimal threshold for voltage diagnosis, and the position of faulty cells can be found by optimal threshold. The original idea of the 3-sigma rule method is to overcome the random error caused by the coupling effect of voltage. However, this method cannot avoid the systematic error. In addition, when the monitoring time points are around 10 s, the 3-sigma rule method has difficulty eliminating random errors during these short-term time points.

Compared with non-model-based approaches on artificial intelligence, the entropy method does not rely on an accurate analysis model and expert experience. Moreover, it does not consider complex fault mechanism and system structure. Entropy is the negative value of the log of the probability distribution, which defines information as possible events or messages. The amount of information in each event constitutes a random variable, its expected value or average, and the occurrence of outliers (random error), thus leading to an increase in entropy. Most of the studies on cell inconsistencies based on entropy method focus on the fault diagnosis of E-vehicles. A general process based on entropy means that entropy algorithm is used to detect the failure of battery cells, and the module-level and cluster-level entropy algorithms are used to evaluate the overall inconsistency of each module and each cluster cell, respectively. Many works verified the capability and effectiveness of the algorithm in fault diagnosis and inconsistency evaluation [32], [33], [34]. Li et al. [33] designed a multi-step advance prediction model based on mean entropy and correlation vector machine (RVM) and applied it to the health state (SOH) and remaining life prediction of batteries. Wang et al. [16] designed a voltage fault diagnosis method based on improved Shannon entropy and found a safety management strategy based on the
Z-Score method. However, in real-time operation, they did not accurately locate the abnormal cell of a power battery. Sun et al. [35] proposed a diagnostic method using Shannon entropy to process the measured data after wavelet transform. Liu et al. [36] proposed that Shannon entropy and the coefficient of variation (CV) rule [37] were used to locate the position of abnormal batteries. However, the disadvantage of the Shannon entropy was easily affected by random error, which led to the misidentification of a faultless battery as the fault state. Given that the entropy method does not rely on an accurate analysis model and expert experience and does not consider the complex fault mechanism and system structure, it has been proven to be greatly suitable for voltage inconsistency. Thus, this study proposed a hybrid permutation entropy method based on Liu et al.’s [36] idea and attempts to detect potentially abnormal changes in cell voltage. Furthermore, when the fault occurs, the next step is to find the optimal positions of cells that may have fault for maintenance or timely replacement rather than replacing the whole battery group. The idea of our work is multiscale permutation entropy (MPE) [38], which is introduced to fuzzify the few outliers in the cell voltages and then evaluate its randomness. In the calculation of this step, the phase space of the original cell voltages is reconstructed, and the random error can be blurred or eliminated to overcome the random error. If the MPE detects a fault in the battery group, the CV rule is used to locate the faulty cell position. The main contributions are as follows:

1) The results of the proposed approach reveal that the existence of faulty cells magnifies the inconsistency between cells, and the method is proven to be effective in the evaluation of inconsistency through the verification of voltage parameters. Moreover, this method is for detecting potential abnormal changes in the cell that is not affected by outliers and solving the shortcoming of random error affecting misjudgment.

2) The proposed method can not only conduct state evaluation by fault diagnosis, but it can also locate the position of faulty cells by the CV rules. Our work is conducive to improving the accuracy of fault diagnosis in practical working conditions.

The remainder of the paper is organized as follows. Section 2 introduces the framework of battery diagnosis. Then, Section 3 proposes the empirical analysis and results of the fault diagnosis approach. Lastly, Section 4 summarizes the paper and provides suggestions for future research.

II. PRELIMINARIES

A. METHODS

1) PROBLEM SETTING

Entropy depends on more probability distribution parameters than variance and is associated with higher-order moments. Thus, it can provide better characterization of uncertainty and better prediction. A higher entropy indicates that the data are scattered. Conversely, the smaller the entropy is, the less the data change will be. To study the battery fault diagnosis of the E-vehicle, the data of batteries are exported from the data platform for further judgment and screening. In this study, the terminal voltage of the battery is selected for processing and analysis, and the terminal voltage data obtained from the monitoring center are in the format of a matrix.

We assume that the matrix is composed of the battery voltage and the running state of the battery at a time point. Then, we set the time range \(t(t_1, t_2, \ldots, t_n, n \in N^*)\). Moreover, \(j (i = 1, 2, \ldots, N)\) cells are used for voltage data collection of the E-vehicles at each time point.

2) FAULT DIAGNOSIS

According to the data format and algorithm, the proposed model is mainly divided into the diagnostic model and the positioning model. In this step, the MPE is used to evaluate the state of the battery by the closest threshold, which is obtained through multiple rounds of screening. The basic process of the diagnosis model is shown as follows:

Step 1: Suppose the specific time \(T \in \{t_1, t_2, \ldots, t_n\}\) and \(j\) cells, then sequence \(X\) is constructed:

\[
X = \begin{bmatrix}
X_{11} & X_{12} & \ldots & X_{1N} \\
X_{21} & X_{22} & \ldots & X_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
X_{T1} & X_{T2} & \ldots & X_{TN}
\end{bmatrix},
\]

(1)

Then, filter and find the driving state of vehicles. Next, update sequence \(X\), and a new sequence \(X_T^{(1)}\) is obtained:

\[
X_T^{(1)} = (X_{11}, \ldots, X_{T,N})
\]

(3)

Step 2: To reconstruct phase space \(X_T^{(1)}\), \(m\) is set as the embedded dimension, \(\lambda\) is the time delay factor, \(r\) is a positive integer, and \(1 < r \leq t - (m - 1)\). \(X_T^{(1)}\) is equal to \(x(i), i = 1, 2, \ldots, N\). Then, coefficients \(\lambda\) and \(r\) are added to create a new sequence space: (4), as shown at the bottom of the next page, where \(m\) is the embedded dimension.

The symbol sequence for \(X(1), X(2), \ldots, X(t-(m-1)\lambda)\).

\[
X(r) = \{x(r), x(r+\lambda), \ldots, x(r+(m-1)\lambda)\}
\]

(5)

where \(x(r+(j_1 - 1)\lambda) \leq x(r+(j_2 - 1)\lambda) \leq \ldots \leq x(r+(j_m - 1)\lambda)\).

\(P\) is the frequency of \(Q(*)\) and MPE \((x(i))\) is calculated as follows:

\[
HP(x(i)) = -\sum_{r=1}^{t-(m-1)\lambda} P_r \ln P_r
\]

(6)

\[
MPE(x(i)) = HP(x(i)) / \ln(m!)
\]

(7)

Eq. (7) is the standardization of Eq. (5). Here, the value of the embedded dimension \(m\) is important to the calculation of MPE. Bandt and Pompe [38] suggested that the range of
embedded dimension $m$ should be within [3], [7], which can fully retain the original information of the sequence.

Step 3: Assume that cell MPE $MPE \left( X_{1}^{(1)} \right), \ldots, MPE \left( X_{n}^{(1)} \right)$, then calculating the mean value and standard deviation at specific time point $^\ast$. The daily threshold of the cell is calculated as follows:

$$\theta^{(\ast)} = \text{mean} \left( MPE \left( X_{1}^{(1)} \right), \ldots, MPE \left( X_{n}^{(1)} \right) \right) + 3 \ast \text{std}(MPE(X_{1}^{(1)}), \ldots, MPE(X_{n}^{(1)}))$$

$$\theta = \min(\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(n)})$$

We only use the upper bound of the 3-sigma rule as threshold because MPE is a positive number. Moreover, a smaller MPE entails less difference between the cells, which is applicable to the diagnostic rule of voltage inconsistency. Each value in Eq. (9) is compared and minimum value is selected as threshold. When any cell’s MPE value exceeds the threshold, the battery is identified as potentially faulty. Then, the CV rule is utilized to find the positions of the faulty cell.

3) POSITION BACKTRACKING

A vehicle is identified as potentially faulty by the diagnostic model by calculating the Gaussian distribution of each column vector $X_{1}^{(1)}, \ldots, X_{T}^{(1)}$:

$$X_{T,1}^{(1)} \sim (\mu_{T,1}^{(1)}, \sigma_{T,1}^{(1)}), \ldots, X_{T}^{(1)} \sim (\mu_{T,N}^{(1)}, \sigma_{T,N}^{(1)})$$

Using the mean and standard deviation of each cell voltage to calculate its CV rule, the CV is defined as follows

$$CV = \mu / \sigma$$

(11)

Then calculate the mean and standard deviation of sequence $CV_{T,1}^{(1)}, \ldots, CV_{T,N}^{(1)}$ and get its Gaussian distribution $CV_{T}^{(1)}$.

$$CV_{T}^{(1)} \sim (\mu_{T}^{(1)}, \sigma_{T}^{(1)})$$

(12)

$\mu_{T}^{(1)} \pm 3\sigma_{T}^{(1)}$ is the threshold to find the position of faulty cells. If the CV value exceeds this threshold, then the position of this cell is regarded as the fault location.

**B. SCHEME OF PROPOSED MODEL**

Using permutation entropy is efficient for testing abnormal data and has great advantages in engineering practice. However, battery voltage data do not follow a normal distribution because they are not random variables in the interaction between batteries. To solve this problem, a new abnormal battery fault diagnosis method is needed to find abnormal batteries of cells. Therefore, a battery fault diagnosis model with different distribution is established. The scheme of the proposed model is shown in Fig. 1, and it consists of two main implementation phases:

1) PHASE 1: MPE IS CALCULATED BY PHASE SPACE RECONSTRUCTION

The fault state of lithium battery is judged according to the optimal threshold, which is calculated by MPE and the 3-sigma rule. Calculating the daily threshold, and select the lowest threshold as the fault diagnosis threshold.

2) PHASE 2: USING THE CV RULE TO TRACKING THE POSITION

The threshold $\mu_{T}^{(1)} \pm 3\sigma_{T}^{(1)}$ and $CV_{T,1}^{(1)}, \ldots, CV_{T,N}^{(1)}$ are calculated by the CV rule. The $CV_{T,1}^{(1)}, \ldots, CV_{T,N}^{(1)}$ and $\mu_{T}^{(1)} \pm 3\sigma_{T}^{(1)}$ are...
\[ 3\sigma T^{(1)} \] of each cell are compared. When \( CV_{T}^{(1)} \) is greater than \( \mu_{T}^{(1)} \pm 3\sigma_{T}^{(1)} \), the \( j \)-th cell is considered faulty.

### III. THE EMPirical ANALYSIS

#### A. THE VOLTAGE FAULT PROGNOSIS

The data are collected from CRRC Electric Vehicle Co., Ltd., which owns the cloud smart platform (as shown in Fig. 2) for big data. The cloud smart platform closely links people, vehicles, and the environment, and it provides the “strongest brain” for E-vehicles. It can effectively manage vehicle safety by standardizing driver behavior and battery system management through this platform. The data of the battery system mainly cover vehicle position and speed, battery system status, etc., such as total voltage and current of battery system, SOC, voltage, and temperature of battery pack characteristic points.

Experimental subjects are three real-time E-vehicles, and the battery group of the three vehicles are all composed of 174 battery cells. This experiment shows that the user has driven a certain mileage. The sampling environment only considers the driving state, and the sampling frequency is 10 s. Vehicle 1 is an accident vehicle, and the data recording time is from July 12, 2019 to August 11, 2019, in which the vehicle broke down on August 11. Vehicle 2 is a fault-free vehicle, and the data recording time is from May 5 to May 20, 2020. Vehicle 3 is a faulty vehicle, and we only use the data on the day of the accident for experimental comparison and analysis. In experiment, the parameters setting is \( m = 6 \) and delay time of permutation entropy \( \lambda = 1 \).

First, Fig. 3 clearly demonstrates that in the 29 days before the accident of vehicle 1, the voltage of each cell mainly fluctuated around 3.4, and the highest value fluctuated around 3.65 (as shown in Fig. 3(a)). Meanwhile, the voltage on the day of the accident was similar to that of the previous 29 days, fluctuating around 3.4. However, Fig. 3(b) shows that its highest value always fluctuates around 3.6, and the number of peaks is more than that of Fig. 3(a), thus indicating many cases of inconsistent voltages.

By observing the MPE information in Fig. 4, the threshold calculated by Fig. 1 is 0.2508. Then, we find that a large number of cells had about 10 obvious MPE peaks before breaking down, which exceeded the MPE threshold around the 28th cell. On the day of the accident, the MPE values of all cells were higher than the threshold we set. This outcome indicates that the first 29 days are a period of failure generation. In this process, the defective cells with problems may gradually cause irreversible damages on other cells through temperature. Therefore, we reasonably believe that the voltage abnormality is not an accidental phenomenon. Instead, voltage instability develops over a certain period, which eventually leads to breakdown.

After diagnosis work by MPE threshold, the fault can be located by the CV rule. An abnormality is found in the CV information of the 109th battery cell. The CV value of the 109th battery cell is about 0.0124, which evidently exceeds the CV upper limit we set. In fact, after the vehicle accident, 109th cell was found to have been damaged and many possible failure cells existed in group. According to the

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**TABLE 1. The information of cell 109.**

| Information                      | Cell 109 |
|----------------------------------|----------|
| Maximum voltage                  | 3.63     |
| Minimum voltage                  | 3.28     |
| Mean                             | 3.4059   |
| MPE-3sigma threshold             | 0.2508   |
| MPE (before broken down)         | 0.2127   |
| MPE (in accident day)            | 0.5482   |
| CV-3sigma threshold              | 0.0121   |
| CV (in accident day)             | 0.0124   |

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FIGURE 3. (a) presents voltage information of the vehicle 1 cells 29 days before the accident, (b) voltage information of the vehicle 1 cells on the accident day, respectively.

MPE experiment, many voltage peaks had occurred in many cells, and all cells exceeded the MPE threshold. As shown in Table 1, the information of the 109th cell can fully verify the effectiveness of the proposed method.

B. VALIDATION

This section introduces vehicle 2 and vehicle 3 to verify the proposed method. Given that vehicle 2 does not have any faults, the MPE information of cells and the daily MPE information of vehicle 2 are calculated. In Fig. 6 (a), the MPE threshold is 0.5786, and all peaks are below the threshold, which indicates that the vehicle does not have any possible failure for the time being. We further verify this opinion through the daily PEC of vehicle 2. As shown in (b), daily average MPE is 0.7213, the standard deviation is 0.0188, and the threshold value is 0.7777. Daily MPE are all lower than 0.7777, thus indicating that vehicle 2 is in a healthy state.

Then, to prove that our model has better performance than other well-known methods further, the CV method and the Shannon entropy method are used to compare with the proposed model. As shown in Fig. 7 and Fig. 8, both the CV method and the Shannon entropy method find that the evaluation values of the 44th to 48th cells have exceeded the set upper threshold (CV upper threshold is 0.0088, and Shannon entropy method upper threshold is 0.1584), which means these cells are faulty. This conclusion is contrary to actual observation. The reason for the erroneous judgement is probably that the battery generates random errors during operation, and the MPE method reduces the possibility of random errors through the phase space reconstruction process. However, the CV method and the Shannon entropy method do not have this step. Hence, the diagnosis work of these methods is easily affected by random error.

Next, the effectiveness of the proposed method is verified again from the empirical analysis of faulty vehicle 3. We use the data of vehicle 3, which broke down on January 5, 2020, to compare and analyze the proposed model, CV method, and Shannon entropy method.
Figs. 9 to 11 show the voltage information, MPE information, and CV fault location information of vehicle 3. In the voltage condition information, the voltage is higher among the first to 80th cell batteries, and the highest cell voltage value of the battery is in the 38th cell. Based on calculation of historical data, mean MPE is 0.2014, the standard deviation
FIGURE 6. (a) presents MPE information of the vehicle 2 cells, (b) daily MPE information of the vehicle 1 battery on the accident day, respectively.

is 0.0104, and the threshold is 0.2326. In Fig. 10, the MPE values of the 13th, 36th, 58th, 136th, and 157th cells all exceed the threshold, thus indicating that individual battery failures have occurred in the battery. From the CV fault location information in Fig. 11, most of the faults occur in the first 80 cells, which is consistent with the position of the

FIGURE 7. CV method of cells within 14 days of vehicle 2.
cell where high voltage values appear. It indicates that the failure of these cells may gradually affect the adjacent cells and eventually lead to a large area of failure step by step.

The results of the Shannon entropy method are shown in Fig. 12. The Shannon entropy values of the first 80 cells greatly exceeded the set threshold (0.2194), which...
is consistent with result of the proposed method. Then, the fault location is determined by the Shannon entropy method. Interestingly, most of the first 80 cells are regarded faulty cells. From the 130th cell to the 160th cell, some cells are also considered faulty. The Shannon entropy method has been proven to be more sensitive than the proposed method to locate the faulty cell perhaps because this method is vulnerable to random errors. When the battery breaks down, some outliers and real fault information are exhausted from the data, which can be obtained by the Shannon entropy method as much as possible.

The model comparison shows that the proposed method can effectively overcome individual voltage anomalies caused by random errors and thus reduce the probability of misestimating vehicle faults. Second, the CV rule and the Shannon entropy method is not applicable to E-vehicle battery fault diagnosis because this method is prone to misjudgment by accidental voltage instability. The MPE methods combined with the CV rule can effectively avoid these errors and overcome the shortcomings, and make optimal faulty cells location.

IV. CONCLUSION

This work develops a voltage fault diagnosis method based on MPE and CV rules, mainly for fault diagnosis and fault location based on voltage inconsistency. The failure threshold is calculated by the MPE of cells and by combining the 3-sigma rule and then compared with the voltage of cells. When the voltage of individual cells exceeds the threshold, the battery group is prone to failure. The idea of MPE is
to calculate the probability of the outlier’s existence, which means that the increase of the number of outliers leads to the increase of the MPE value.

Herein, the size, capacitance, and other parameters of every cell on the same battery group must be consistent. Thus, the huge differences between the cells can be captured by the 3-sigma rule. To find the location of the faulty cell, this study has selected the CV method for this work. The CV method has strong sensitivity to faulty cells and can accurately locate the position of these cells. However, the CV method and the Shannon entropy method cannot be directly used for fault diagnosis. These methods are vulnerable to random errors within the battery group and thus produce wrong results.

Moreover, all analyses and results are based on the actual monitoring data of the Yunzhitong platform of CRRC Electric Vehicle Co., Ltd. It can accurately reflect the battery health status of E-vehicles in actual operation. Experiments show that this method can avoid the influence of random errors and obtain accurate fault diagnosis results. Second, the abnormal cell position can be effectively detected. Third, the proposed method does not rely on an accurate analysis model and expert experience and does not consider the complex fault mechanism and system structure. Finally, apart from the voltage inconsistency, temperature and driving behavior can also be detected by the proposed approach in the future. These variables are of great significance for our future research.

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