Discharge curve-based formation of retired power batteries for secondary use

Ziyu Xiao* and Siqi Wu
Hubei Key Laboratory for High-Efficiency Utilization of Solar Energy and Operation Control of Energy Storage System, Hubei University of Technology, Wuhan, 430068, China

Abstract
To address the problem of optional group formation in the process of retired power batteries for secondary use, a detection method based on the ampere-time integration method is used for batch testing of retired power batteries. The dynamic time-bending dynamic time warping distance between different batteries is calculated by comparing the discharge curves during the testing process. Combining the remaining capacity, open circuit voltage and internal resistance of the battery as a common battery classification condition, each condition is normalised and a density canopy $+ K$-means clustering algorithm is applied to regroup the retired power batteries. This method improves the regrouping technique for the retired batteries and improves the performance of the regrouped battery modules in terms of capacity and consistency.

Keywords: retired li-ion batteries; classification algorithms; discharge curve; dynamic time warping

1. INTRODUCTION
Electric vehicles use lithium-ion batteries, which need to be retired when their capacity decays below 80% to ensure operational safety and mileage. As a result, retired lithium-ion batteries still have $\sim 70$–80% of their nominal capacity and are available for use in other applications, such as energy storage for smart grids using renewable power, or to power base stations and other small devices [1–7]. By 2020, the number of lithium-ion batteries retired globally will exceed 25 billion per year. By 2035, the number of battery packs available for upcycling will increase to 6.8 million. By 2035, the global market for the secondary use of retired batteries is expected to grow from US$16 million in 2014 to US$3 billion. Therefore, the secondary use of retired batteries can be foreseen as a very promising market [8–12].

As a large number of power batteries are retired from power vehicles, retired power batteries need to be used for secondary use, but the safety and traceability of retired power batteries are difficult to ensure, and the inconsistency of parameters (capacity, internal resistance, voltage, etc.) between retired power battery units is high, so direct secondary use may lead to the specific energy and specific power of the battery system being much lower than the level of the individual units, which not only causes waste of resources but also easily leads to overcharging and overdischarging between units within the module, causing thermal runaway and even spontaneous combustion, which is very dangerous. It is also easy to cause overcharging and overdischarging between the individual cells within the module, resulting in thermal runaway of the battery and even spontaneous combustion, which is very dangerous. Therefore, the key to the secondary use of retired power batteries is to solve its consistency problem.

To address this problem, current research has focused on two main areas: battery equalisation technology based on external power electronic circuits [13–16] and consistency sorting technology for the batteries themselves [17–18]. Considering the high degree of inconsistency of retired power batteries, the equalisation circuit topology and control strategy will be more complicated when directly forming into groups for secondary utilisation. Therefore, in order to effectively reduce the complexity of the equalisation circuit when forming into groups, it is necessary to perform consistency sorting of retired power batteries before forming into groups.

Consistency sorting of batteries is essentially the purpose of battery grouping, which is to classify batteries based on their differences in various characteristics. These characteristics include mainly static capacity, voltage, internal resistance and thermal behavior. By analyzing the similarity of one of these characteristics, the grouping of batteries can be achieved. The static capacity

International Journal of Low-Carbon Technologies 2021, 00, 1–8
© The Author(s) 2021. Published by Oxford University Press.
This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (http://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com
doi:10.1093/ijlct/ctab010
based grouping method in the literature [17] performs charge and discharge tests under specific conditions and calculates the static capacity based on the charge and discharge times. The batteries are then grouped according to their respective static capacities. The advantage of this method is that it is easy to use, but it is susceptible to environmental factors such as temperature. The voltage-based grouping method in the literature [18] classifies batteries into different groups based on their open-circuit or load voltages. Although measuring the voltage is simple and straightforward, the grouping results are usually unsatisfactory because the voltage variation during charging and discharging is ignored. In contrast, the grouping method based on internal resistance in the literature [19] yields cells with better consistency, while accurate measurement of internal resistance is difficult.

Each of the previously mentioned grouping methods has advantages and disadvantages. To improve these shortcomings, in practical applications, manufacturers often combine two or more methods to obtain better grouping performance [20]. In the literature [21–22] self-organizing mapping is used for battery grouping based on battery temperature and capacity. The demonstrated grouping experiments demonstrated its effectiveness in reducing the variation of the above two parameters. However, this combined approach leads to more complex operations and longer execution times, but still cannot escape from the drawbacks of the basic approach.

To address the above needs and research status, this paper proposes a consistent sorting method for retired batteries based on the extraction of dynamic characteristic parameters from the discharge curve of the battery.

Firstly, static characteristic parameters such as residual capacity, internal resistance and open circuit voltage (OCV) of single cell batteries are considered comprehensively; secondly, a clustering algorithm is used to initially classify single cells; again, the dynamic characteristic parameters are extracted for classification by combining the discharge curves of single cells; finally, it is validated by experiments.

2. **DECOMMISSIONED BATTERY DATA**

For the capacity test of retired battery packs, 10 lithium-ion battery packs for retired electric vehicles were used in this test. They consist of 50 Ah single cell batteries in six parallel and four strings. The factory rated capacity is 300 Ah with a maximum charge current of 0.5 C and discharge current of 1 C.

According to the charge and discharge capacity data of the 10 battery packs shown in Table 1, their capacity at the time of retirement was ~65% to 81% of the factory nominal capacity, with a difference of 46.8 Ah between the 3# battery pack with the largest remaining capacity and the 9# with the smallest remaining capacity. Based on the fact that lithium-ion batteries used in electric vehicles need to be retired when their capacity decays to less than 80%, the 3# and 7# battery packs with a capacity retention rate greater than 80% were dismantled for subsequent research.

### Table 1. Capacity test data for decommissioned battery packs.

| No. | Charging capacity/Ah | Discharge capacity/Ah | Capacity retention/% |
|-----|----------------------|-----------------------|----------------------|
| 1#  | 219.6                | 219.4                 | 73.13                |
| 2#  | 236.5                | 235.4                 | 78.47                |
| 3#  | 240.7                | 243.1                 | 81.04                |
| 4#  | 204.1                | 202.4                 | 67.46                |
| 5#  | 222.9                | 220.6                 | 73.53                |
| 6#  | 231.1                | 228.8                 | 76.26                |
| 7#  | 242.0                | 240.2                 | 80.07                |
| 8#  | 235.7                | 235.2                 | 78.41                |
| 9#  | 197.5                | 196.3                 | 65.43                |
| 10# | 234.7                | 234.6                 | 78.22                |

2.1. **Extraction of static characteristic parameters**

The 48 individual cells of the 3# and 7# battery packs were tested independently for the following: 1. ohmic internal resistance, taking the ohmic internal resistance value of SOC discharged at 50%; 2. discharge capacity; 3. OCV, which is the OCV value measured after charging to SOC 100% at rated current and left for 10 minutes, to obtain the static characteristics as shown in Table 2 and Table 3.

2.2. **Extraction of dynamic characteristic parameters**

2.2.1. **Dynamic time-bending distances**

The dynamic time warping (DTW) method is used for pattern recognition in sequence time, and DTW employs dynamic programming (DP) to perform time-regularisation calculations, which is a measure of the degree of similarity between time series of different lengths. DTW is widely used in various fields such as template matching, data mining and information retrieval [23].

Given a time series of $X = \{x_1, x_2, ..., x_m\}$ and $Y = \{y_1, y_2, ..., y_n\}$, then the sequence $X$ and the sequence $Y$. The dynamic time-bending distance between is $D(X, Y) = f(m, n)$, where $f(m, n)$ is calculated as follows:

$$
\begin{align*}
  f(0, 0) &= 0; f(i, 0) = f(0, j) = \infty; f(1, 1) = a_1; \\
  f(i, j) &= a_q + \min\{f(i-1, j), f(i, j-1), f(i-1, j-1)\} \\
\end{align*}
$$

Through DP, the path with the smallest cumulative distance can be found in the distance matrix between time series subject to certain constraints. The minimum cumulative distance is the DTW distance, which reflects the degree of similarity between the sequences; the smaller the DTW distance, the more similar the sequences are, and vice versa.

2.2.2. **Dynamic time bending distance of the discharge curve**

The distance between the discharge curves of the two battery monoblocks was calculated using the data from the discharge curves based on the ampere-time integration method measurements, combined with the dynamic time bending method. The discharge curves of the two batteries are shown in Figure 1.
Table 2. Static characteristics data of individual cells in 3# battery pack.

| 3# battery pack | Ohm internal resistance (mΩ) | Discharge capacity (Ah) | Open circuit voltage (V) |
|----------------|-------------------------------|-------------------------|-------------------------|
| 1              | 1.8                           | 40.33                   | 4.12                    |
| 2              | 2.0                           | 38.64                   | 4.24                    |
| 3              | 2.1                           | 38.26                   | 4.01                    |
| 4              | 1.6                           | 41.06                   | 4.07                    |
| 5              | 2.2                           | 38.73                   | 3.83                    |
| 6              | 2.1                           | 39.34                   | 4.02                    |
| 7              | 2.1                           | 38.41                   | 3.86                    |
| 8              | 1.7                           | 40.55                   | 3.82                    |
| 9              | 2.0                           | 40.16                   | 4.04                    |
| 10             | 2.3                           | 38.16                   | 4.02                    |
| 11             | 1.8                           | 41.22                   | 3.97                    |
| 12             | 1.9                           | 38.06                   | 4.12                    |

Table 3. Static characteristics data of individual cells in 7# battery pack.

| 3# battery pack | Ohm internal resistance (mΩ) | Discharge capacity (Ah) | Open circuit voltage (V) |
|----------------|-------------------------------|-------------------------|-------------------------|
| 1              | 1.8                           | 38.19                   | 3.81                    |
| 2              | 2.2                           | 38.47                   | 4.11                    |
| 3              | 2.1                           | 39.69                   | 4.18                    |
| 4              | 2.6                           | 38.64                   | 4.13                    |
| 5              | 1.9                           | 40.53                   | 4.19                    |
| 6              | 1.9                           | 38.9                    | 3.87                    |
| 7              | 2.1                           | 40.8                    | 3.82                    |
| 8              | 1.8                           | 40.9                    | 4.11                    |
| 9              | 2.2                           | 38.23                   | 4.01                    |
| 10             | 1.8                           | 40.48                   | 3.96                    |
| 11             | 2.1                           | 38.84                   | 4.22                    |
| 12             | 2.1                           | 38.21                   | 4.08                    |

The time series during the discharge of the two battery monoblocks after the DTW process is shown in Figure 2. The dynamic time bending distance is used as a health factor, together with the battery capacity, OCV and internal resistance health factors to provide the basis for subsequent clustering groupings.

3. DENSITY CANOPY + K-MEANS BASED ALGORITHM FOR CELL REORGANIZATION

3.1. Density canopy + K-means algorithm

The K-means algorithm is a well-known divisional clustering algorithm. Due to its concise computational process and high efficiency, the K-means algorithm is one of the most widely used divisional clustering algorithms and is widely used in machine learning statistics as well as marketing [24]. However, the initial clustering centres of the traditional K-Means algorithm are chosen randomly, so outliers and noise can easily affect the clustering results, and it is easy to fall into local minima.

The density canopy + K-means algorithm for clustering feature data is used to address the problem that K-means cannot determine the number of clusters and the initial cluster centres are chosen randomly. The most suitable initial cluster centres and clusters are used as input parameters for the K-means algorithm, and then the K-means algorithm is used to perform ‘fine’ clustering to improve the final clustering effect of the K-means algorithm.
The core of the algorithm lies in the use of density. For the data set
$D = \{ x_1, x_2, \ldots, x_m \}$, the average distance between all samples is first calculated by formula 2.

$$MeanDis(D) = \frac{2}{m(m-1)} \sum_{i=1}^{m} \sum_{j=i+1}^{m} d_{ij}(x_i, x_j)$$  \hspace{1cm} (2)

where $d_{ij}(x_i, x_j)$ denotes $x_i$ the distance between $x_j$ the distance between $x_i$ and $x_j$.

The average density formula 3 is then used to calculate each sample in the data set $D$.

$$\rho_i = \sum_{j=1}^{m} f (d_{ij} - MeanDis(D))$$  \hspace{1cm} (3)

where $f(x) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases}$. The sample with the greatest density is then $C_i$ as the first clustering centre into the set $C$ in ($C = \{ C_1 \}$) calculates the distance from the remaining samples to $C_1$ distance, and if it is less than the average distance then move from $D$ in the set is moved into the $C_1$ as the centre of the cluster. Calculate $D$ the average density of the remaining samples in the cluster, and the sample with the highest density is used as the second cluster centre $C_2$ into the set $C$ in ($C = \{ C_1, C_2 \}$) and again calculate the distance between the remaining samples and $C_2$ distance, and those less than that distance are moved into the $C_2$. The remaining samples are moved into the cluster centered on the cluster, and so on, until $D$ the data in it are empty. The resulting set of centroids is then used $C = \{ C_1, C_2, \ldots, C_k \}$ as the initial centroids to execute the K-means algorithm.

The centroid set samples $x_j (x_j \in C_j)$ and the respective center-of-mass vector $C_j (j = 1, 2, \ldots, k)$ the distance between

$$d_{ij} = \|x - \mu_i\|_2^2$$  \hspace{1cm} (4)

for $C_j$. Recalculate the new centre of mass for all sample points in

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$$  \hspace{1cm} (5)

If all the $k$ mass vectors have not changed, then it is over. Density canopy + K-means algorithm improves on the random selection of the centre of mass, which is susceptible to outliers and noise and falls into local minima. It also uses density to make clustering more accurate.

### 3.2. Data standardisation

Data standardisation is a basic task in processing data. Different evaluation indicators often have different magnitudes and magnitude units, such a situation will affect the results of data analysis, in order to eliminate the influence of the magnitude between indicators, data standardisation is needed to solve the comparability between data indicators. After the original data have been standardised, the indicators are in the same order of magnitude and suitable for comprehensive comparative evaluation.

Min–max normalisation, also known as outlier normalisation, is a linear transformation of the original data so that the resulting values map to the range (0,1). The transformation function is as follows:

$$\hat{x} = \frac{x - \min}{\max - \min}$$  \hspace{1cm} (6)

### 3.3. Battery reconfiguration

The static characteristic parameters of the 48 individual cells in section 2.1 were first standardised min–max and then the cells were reorganised using the density canopy + K-means algorithm and the results are shown in Figure 4.

One of the clustering centres was selected and the static data of the batteries in this clustering centre are shown in Table 4.

Because the discharge curve is a relationship between voltage and discharge time, the 9# battery with the same OCV and average value was selected as a reference. The discharge curves of the other batteries were compared with the 9# battery to obtain the DTW distance, and the three batteries with the smallest DTW distance values were selected to form a two-parallel-two-series battery pack with the 9# battery. The discharge curves are shown in Figure 5 and the DTW distances are shown in Figure 6.

Battery group A was sorted according to DTW distance as shown in Table 5.
Considering the consistency of the cells, the 7# cell with the smallest ohmic internal resistance of the remaining five cells is removed and the remaining four cells also form a two-parallel-two-string battery pack B. Then battery pack B is simply classified according to static characteristics, as shown in Table 6.

Finally, the remaining 40 cells with a discharge capacity greater than 80%, i.e. a discharge capacity greater than 40 Ah, also form
4. EXPERIMENTS

4.1. Experimental programme

The static characteristics data for battery packs A, B and C are first extracted as shown in Table 8.

The battery pack is then tested for 1000 cycles and the test flow is shown in Figure 7.

1. Charge and discharge according to 0.5C cycle, check whether the number of times n of this test is less than 100 after each cycle, if it is less than 100 times, continue the cycle test, if the number of tests is equal to 100 times, stop the cycle test and carry out capacity test on.

2. At the end of the capacity test, output the remaining capacity measured on that occasion.

3. Test the OCV value measured when the SOC is 100% and the cell ohmic internal resistance value at 50% when left to stand for 10 minutes.

4. Save remaining capacity, OVC, ohmic internal resistance data.

5. End of cycle test 1000 times.

4.2. Experimental results and analysis

Statistical test data, the remaining capacity of the battery pack after cycle testing is shown in Table 8 and the ohmic internal resistance is shown in Table 9.

As can be seen from Table 9, the residual capacity of battery pack A, selected on the basis of its dynamic characteristics, varies by less than 10%, which is better than that of battery packs B and C. The difference between the static performance of individual cells in battery pack A and battery pack B is not significant, but the
residual capacity of battery pack A is higher than that of battery pack B by 1.96 AH when it is formed into a group.

As can be seen in Table 10, the ohmic internal resistance of the battery pack after 1000 cycles has the smallest rate of change for pack A and the largest for pack C.

As can be seen in Table 11, the OCV of the battery pack will drop after 1000 cycles, and the OCV will fluctuate during the process, which shows that the OCV does not change much.
In summary, the dynamic characteristics of the battery can also be used as a classification indicator in the grouping of retired batteries. A combination of dynamic and static characteristics is more consistent than static characteristics only. However, classification by static characteristics is better than classification by residual capacity.

5. CONCLUSION

(1) The use of dynamic time-bending distance to calculate the distance between retired power batteries is a measure of the dynamic characteristics of the batteries, providing an important basis for the detection of batteries for secondary use and improving the accuracy of the detection.

(2) The data on battery capacity, battery internal resistance, battery charging voltage and the distance between charging and discharging curves obtained from the testing of retired power batteries for secondary use are used as parameters for clustering, fully taking into account the static and dynamic characteristics of the batteries and improving the comprehensiveness of the testing and the consistency of the batteries.

REFERENCES

[1] Wu T, Ji F, Liao L et al. Voltage-SOC balancing control scheme for series connected lithium-ion battery packs. J Energy Storage 2019;25C:100895.
[2] Lai X, Qiao D, Zheng Y et al. A rapid screening and regrouping approach based on neural networks for large-scale retired lithium-ion cells in second-use applications. J Clean Prod 2019;213:776–91.
[3] Ji F, Liao L, Wu TZ et al. Self-reconfiguration batteries with stable voltage during the full cycle without the DC–DC converter. J Energy Storage 2020;101213:28.
[4] Thackeray MM, Wolverton C, Isaacs ED. Electrical energy storage for transportation—approaching the limits of, and going beyond, lithium-ion batteries. Energy Environ Sci 2012;5:7854–63.
[5] Jiang Y, Jiang J, Zhang C et al. State of health estimation of second-life LiFePO4 batteries for energy storage applications. J Clean Prod 2018;205:754–62.
[6] Tong S, Fung T, Klein MP et al. Demonstration of reusing electric vehicle battery for solar energy storage and demand side management. J Energy Storage 2017;11:200–10.
[7] Tong SJ, Same A, Kootstra MA et al. Off-grid photovoltaic vehicle charge using second life lithium batteries: an experimental and numerical investigation. Appl Energy 2013;104:740–50.
[8] Assunção, Moura PS, de Almeida AT. Technical and economic assessment of the secondary use of repurposed electric vehicle batteries in the residential sector to support solar energy. Appl Energy 2016;181:120–31.
[9] Li J, Wang Y, Tan X. Research on the classification method for the secondary uses of retired lithium-ion traction batteries. Energy Procedia 2017;105:2843–9.
[10] Jiang Y, Jiang J, Zhang C et al. Recognition of battery aging variations for LiFePO4 batteries in 2nd use applications combining incremental capacity analysis and statistical approaches. J Power Sources 2017;360:180–8.
[11] Neubauer J, Pesaran A. The ability of battery second use strategies to impact plug-in electric vehicle prices and serve utility energy storage applications. J Power Sources 2011;196:10351–8.
[12] Li W, Long R, Chen H et al. A review of factors influencing consumer intentions to adopt battery electric vehicles. Renew Sustain Energy Rev 2017;78:318–28.
[13] Das UK, Shrivastava P, Kok S et al. Advancement of lithium-ion battery cells voltage equalization techniques: a review. Renew Sust Energy Rev 2020;134.
[14] A Y C, B X L, A T S et al. An any-cell(s)-to-cell(s) equalization method with a single magnetic component for lithium-ion battery pack. J Energy Storage 2020.
[15] Zilberman I, Schmitt J, Ludwig S et al. Simulation of voltage imbalance in large lithium-ion battery packs influenced by cell-to-cell variations and balancing systems—ScienceDirect. J Energy Storage 32.
[16] Turskoy A, Teke A, Alkaya A. A comprehensive overview of the dc–dc converter-based battery charge balancing methods in electric vehicles. Renew Sust Energy Rev 2020;133:110274.
[17] Kim J, Shin J, Chun C et al. Stable configuration of a Li-ion series battery pack based on a screening process for improved voltage/SOC balancing. IEEE Trans Power Electron 2012;27:411–24.
[18] Li X. 2014. A comparative study of sorting methods for lithium-ion batteries. In Transportation Electrification Asia-Pacific. Springer.
[19] Gogoana R, Pinson MB, Bazant MZ et al. Internal resistance matching for parallel-connected lithium-ion cells and impacts on battery pack cycle life. J Power Sources 2014;252:8–13.
[20] Zeng Y, Yang Y, He Z et al. Lead-acid battery automatic grouping system based on graph cuts. Electr Power Compon Syst 2016;44:450–8.
[21] He F, Shen WX, Song Q et al. 2014. Clustering LiFePO4 cells for battery pack based on neural network in EVs. In Transportation Electrification Asia-Pacific. Springer.
[22] Yun L, Sandoval J, Zhang J et al. Lithium-ion battery packs formation with improved electrochemical performance for electric vehicles: experimental and clustering analysis. J Electrochem Energy Conv Storage 2019;16:021011.
[23] Huang S, Hong-Ping L. Classification of temporal data using dynamic time warping and compressed learning. Biomed Signal Process Control 2020;57.
[24] Fard MM, Thonet T, Gaussier E. Deep k-means: jointly clustering with k-means and learning representations. Pattern Recognit Lett 2020;185–92.