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SHORT COMMUNICATION

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Machine learning approach for solving inconsistency problems of Li-ion batteries during the manufacturing stage

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Summary

The inconsistency in the mass production of lithium-ion battery (LIB) packs stem from the inconsistency in the capacity, voltage and internal resistance of single batteries that compose packs. The inconsistency issue of these battery packs can greatly reduce the output performance of a large power pack. This paper proposed the machine learning approach based on self-organization mapping (SOM) neural networks for establishing the consistency of LIBs. This method comprehensively compares and analyzes the real-LIB parameters (internal resistance, capacity and voltage) data obtained during charging and discharging to form the clusters of similar performing LIBs. Experimental result validated the clustering analysis and it indicates that the performance of clustered battery pack typically precedes than that of original. The capacity of clustered battery pack increased 1.9% compared with brand-new pack. The temperature distribution of the battery pack assembled after screening is consistent. The peak temperature is 4°-5° lower than the ordinary battery, and the temperature fluctuation is reduced by 2.6°. In addition, the application of cluster analysis is expanded and some key research directions are pointed out.

KEYWORDS

energy conversion systems, energy storage, hybrid energy systems, lithium-ion cells consistency, machine learning

1 | INTRODUCTION

Transport is one of the largest sources of pollution.[1] In these years, government has strengthened its cleaner automotive policies such as green shipping program to promote green development and reduce harmful exhausts. Shipping on ocean accounts for 90% of international transport. International maritime organization (IMO) is an institution specialized in coordinating the maritime shipping work among countries. It is committed to promote the supervision of maritime safety and environmental protection, ensuring the healthy, green development of the shipping industry.[2,3] However, according to a report by the IMO, the shipping industry currently emits 1 billion tons of CO_2 per year. In other words, the pollutants emitted from the chimney of a large cruise ship are more than 200 times more than the total amount of exhaust emitted by all cars on a congested road. Shipping environmental pollution does not meet the requirements of green development. To that end, IMO has agreed to cut greenhouse gas emissions from ships by 50% from 2009 levels. Battery power has become top choice for many companies while trying to find alternative energy to substitute for fossil fuel utilized in cruise. Lithium-ion battery (LIB) becomes the most widely studied, widely used battery among diversity of batteries due to its huge advantage in capacity, battery energy density, charge and discharge efficiency, etc.[4-6]

At present, some LIBs have been used in the Marine industry and some breakthroughs have been made. LIB has been successfully utilized in maritime equipment, such as cruise ships, automatic guide vehicles and ship unloaders. The process is shown in Figure 1. HH ferries in Sweden has planned and begun to make fully 10 000-V automated connections for some large ferries in Europe. When these programs finish, it will be much quickly to charge for these ferries by battery power only which is less than 5 minutes. Massimo Guarnieri et al in Massimo Guarnieri University of Padua attempt to realize the combination of diesel engine and LIB to impel the electric water bus business to be prosperous. According to their calculations and imaginations, the development of hybrid water buses could be boosted by a modest infrastructure investment. This type vaporetti has made peak service rate dropped from 147 to 65 kW that is a little higher than average. This research is of great economic value to Venice, a city with frequent water transportation. Ancona et al built an energy distribution system for electric ships contributing to energy saving and environmental protection, reducing CO_2 emissions by 20% annually. The application of LIBs in Marine industry is still in the preliminary stage. More research is needed to improve the efficiency and endurance of battery drives. Battery cruising ability depends on the energy density of single battery and battery pack consistency (capacity, internal resistance, voltage and temperature). The research problem of inconsistent battery packs is particularly acute on large cruise ships. In general, batteries are in series and in parallel to improve the voltage and capacity. Usually a battery pack contains hundreds of series-parallel batteries to provide enough output power.[7] The subtle error between individual cells in the battery pack is inevitable to be amplified and this makes open circuit voltage of batteries in series and capacity of batteries in parallel are both less than expected value.[8] There are two main reasons resulting in inconsistency of battery packs. The first one is the different performance of single battery. The second one is that the inconsistency phenomenon exacerbates in use due to the differences between single battery cells. The batteries produced even in the same batch have different capacity and internal resistance.[8] The battery in charge with smallest capacity will stop whole charging process when it is fully charged, which means that the

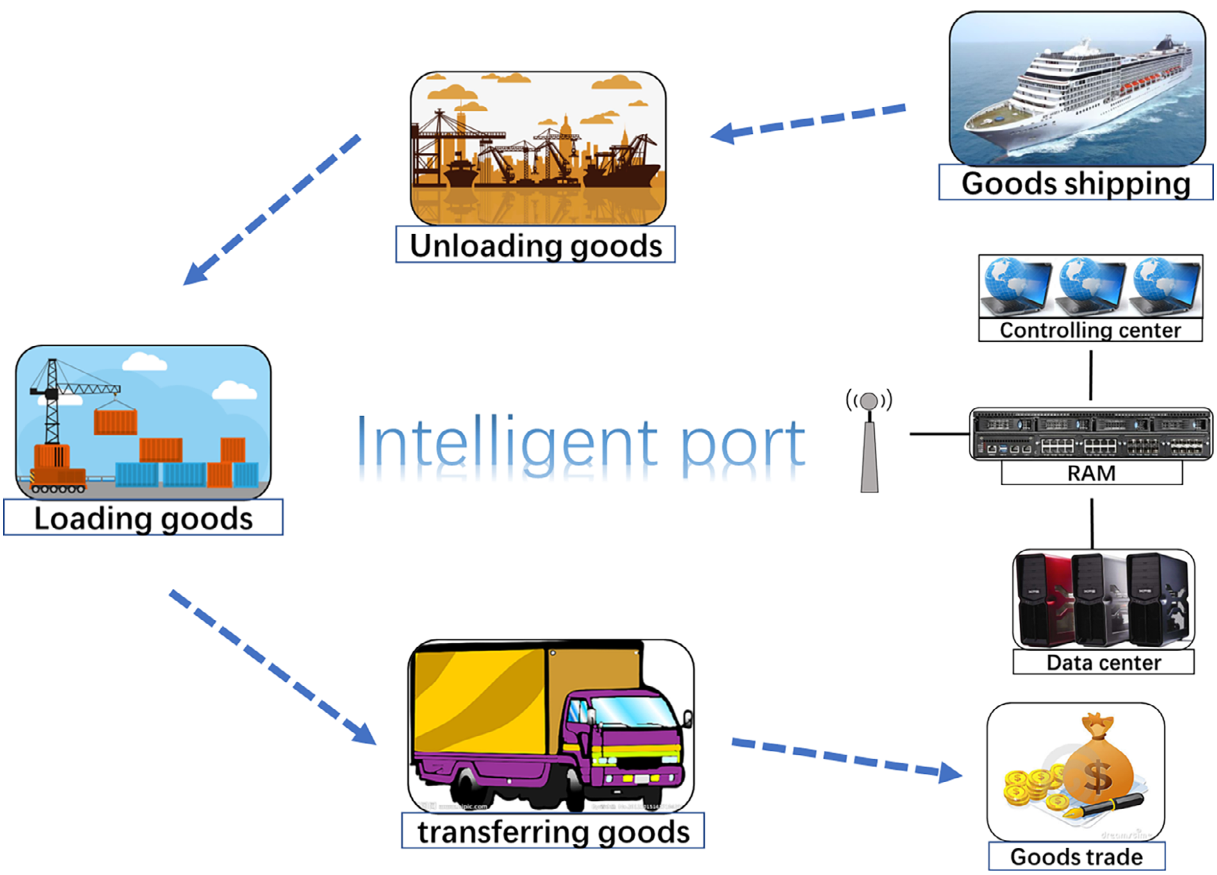

FIGURE 1 Applications of battery in maritime ports industry [Colour figure can be viewed at wileyonlinelibrary.com]

weakest single battery in the battery pack drags down the whole performance of the battery. Figure 2A shows the battery pack delivered by the manufacturer, and there is certain difference in the capacity of single battery. In Figure 2B, we replace the two weaker single batteries in the two series modules to get better performance batteries. The battery capacity increases by 0.01 Ah respectively, but capacity of whole battery pack increases by 0.06 Ah compared with the previous one.

It can be seen improving the consistency of battery packs on cruise ships can greatly promote the development of maritime shipping. An important way to solve the inconsistency problem is to do cluster analysis for the battery. A single battery is divided into groups according to its similarity of the batteries through cluster analysis. And then the battery with high similarity is assembled in a battery pack to improve the overall performance of whole battery pack. In this regard, scientists have also done a lot of in-depth exploration. Wang et al proposed a new quick test sorting algorithm-squeeze algorithm,[5] which obtained partial charge-discharge characteristic curves of 100 batteries through testing and compared them with the curves in the complete database of 1111. They realized clustering of batteries in a short period of time while clustering success rate reached 86%. Paolo Raspa et al used self-organizing graph neural network method (SOM) to cluster homologous batteries. Based on the clustering of battery capacity and discharge voltage, the SOC variability of batteries was reduced by 90% compared with that of randomly combined battery packs.[9] He et al studied the classification method of lithium iron phosphate ($LiFePO_4$) battery based on neural network (NN) and clustered the battery by analyzing its capacity and thermal performance. The maximum voltage inconsistency of the unscreened battery pack is 0.197%. In comparison, the maximum temperature inconsistency of the sorting battery is 0.665% while the temperature inconsistency of unsorted battery pack is 0.95%.[8] While, there exists methods to address the consistency problem, but still there is no optimal configuration achievable for battery pack design. The reasons could be due to lack of measurement of relevant and impactful design variables such as stack stress, internal resistance or inability of computational method to form the battery pack.[9-13] There exists numerous intelligent methods such as those based on image processing,[14] statistical regression methods and evolutionary algorithms such as genetic programming, genetic algorithms, etc.[13-16] However, these methods are either based on statistical assumptions or computational expensive.[17,18] Reliability and feasibility are difficult to satisfy at the same time.

Authors propose the machine learning approach for establishing the consistency of LIBs used in electric vehicles. A self-organization mapping (SOM) neural networks is applied to the LIB parameters (internal resistance, capacity and voltage) obtained during charging and discharging to form the clusters of cells with similar performance. Experiments are then performed to validate the

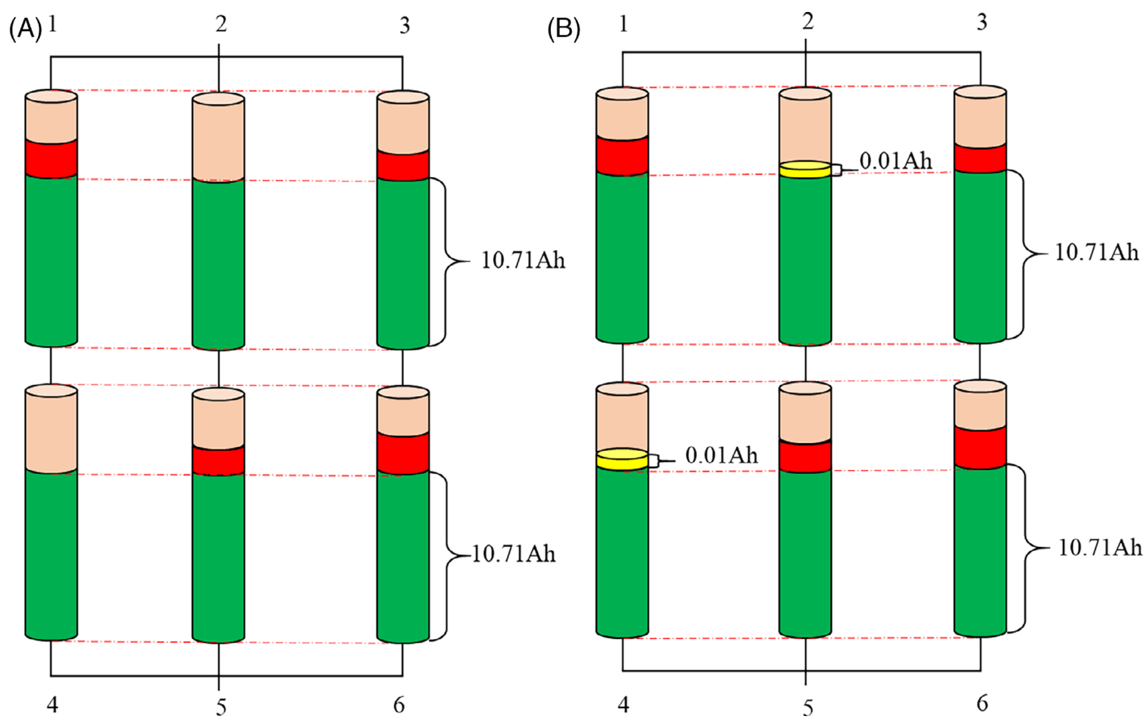

FIGURE 2 The problem of inconsistency [Colour figure can be viewed at wileyonlinelibrary.com]

numerical results. In addition, the application of clustering analysis is expanded, and some critical research directions are pointed out.

2 | RESEARCH PROBLEM

Differences in capacity, open circuit voltage, internal resistance, cycle efficiency and charging and discharging temperature between individual batteries will all affect the inconsistency of battery pack. The inconsistency of LIB pack is the main factor affecting the performance of battery pack. This will also lead to three major problems in the use of LIBs:

1 The total capacity of the battery pack reduces slightly.
2 Battery lifespan is less than expected.
3 Uneven heat results in safety problems (Figure 3).

As illustrated above, the capacity of battery pack depends on the cell with smallest capacity which means the pack could not be fully charged. The capacity of several single cells is not fully utilized and the total capacity of battery pack reduces. The cell with smallest capacity is first fully charged and is also the most easily overcharged. The overcharge rises battery internal resistance and accelerates battery aging. These defects inevitable shorten battery lifespan and cause unexpected safety problems.

To alleviate or even solve these problems, a comprehensive methodology will be proposed. The research objective is cylindrical 18 650 lithium battery packs. The voltage of single cell is 3.6-4.2 V and it is capacity is 2600 mAh. Firstly, the data of 48 single batteries disassembled from four battery packs during charging and discharging are collected. Then, according to the collected data, the batteries are clustered and analyzed with self-organization neural network.

3 | EXPERIMENTAL ANALYSIS

3.1 | Comprehensive experiment and Clustering visualization analysis method

In this study, the battery was firstly analyzed by clustering method. And then a contrast experiment was designed to verify the clustering results. The comprehensive process consists of three stages:

Stage 1: Single-battery data collection. In this stage, five battery packs produced in the same batch by the manufacturing company are taken in which 12 single batteries are contained. Four packs were disassembled and 48 single batteries were taken for use. Other battery pack was left untreated. The Neware battery test system is used to collect the parameters of the battery during its charging and discharging.

Stage 2: Battery clustering analysis. After collecting the charging and discharging performance parameters of each battery, clustering method is used for analysis. SOM is used to cluster the battery by analyzing the capacity, internal resistance, voltage and temperature of the battery.

Stage 3: Assemble the new battery pack and design a comparative experiment. According to the analysis results of the previous step, 12 batteries with superior performance and similar parameters were carefully

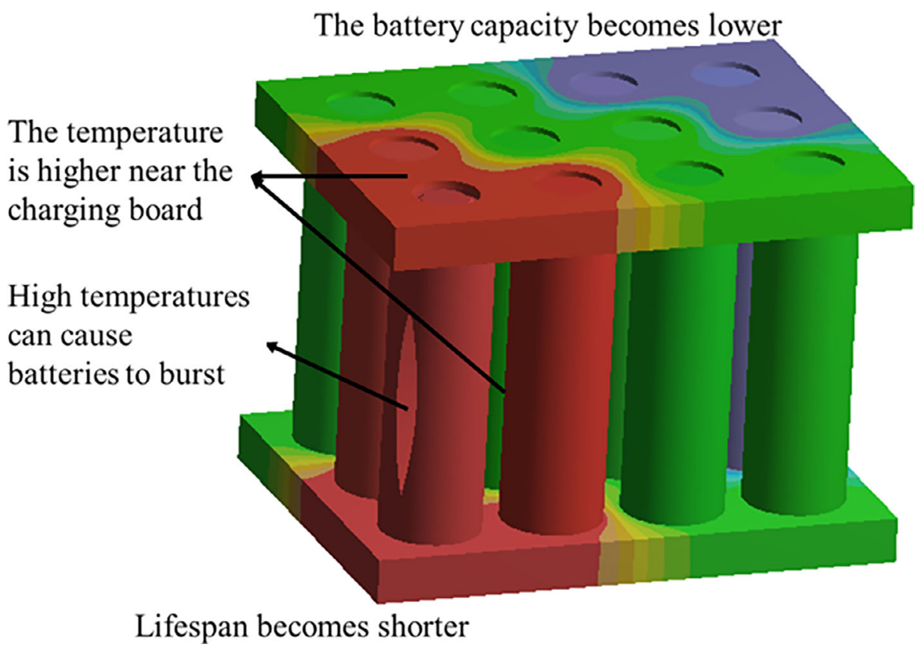

FIGURE 3 Main problems in battery pack [Colour figure can be viewed at wileyonlinelibrary.com]

selected from the 48 batteries to assemble new battery packs. Twelve of the remaining 36 batteries were randomly selected to form the second new battery pack. Comparative experiment is designed to test two newly assembled battery packs and the original battery pack produced by the manufacturing company.

3.1.1 | Single battery test

First, the five battery packs used in the experiment were marked pack A-pack E. Pack A-pack D was dismantled while Pack E not. Cell1-cell48 is the serial number of the battery packs dismantled. Then these batteries are connected to the Neware battery test system in turn to charge and discharge the battery and corresponding data of 20 times charge and discharge is collected. These corresponding data includes charge and discharge voltage, surface temperature, capacity and battery internal resistance where the first three parameters are recorded automatically by Neware battery test system while the internal resistance is measured by battery resistance measuring device. All data is sampled once per second. The details of battery resistance measuring device is shown in Table 1. Battery disassembly process is shown in Figure 4. The testing process is listed in Table 2 and these four steps recycled for 20 times. It can be seen there are some differences between batteries in the same battery pack. Inevitably, there are inconsistencies in the battery packs.

3.1.2 | SOM clustering analysis

Self-organizing mapping neural network (SOM) is an unsupervised neural network based on competitive learning. It was proposed by Kohen in 1981. Due to the rapid development of neural network in the 1980s, SOM theory was widely developed. SOM explores the internal structure and essential attributes of samples by automatically searching where the network can self-organize and self-adapt to change its own network structure and parameters for better mapping. This characteristic makes SOM have strong self-learning ability.[19,20] Its outstanding advantage is that it cannot only learn the distribution of the input vector, but also learn the topology of the input vector. SOM method is used here for battery clustering analysis. Parameters that need to be trained and learned are charge and discharge voltage, surface temperature, battery internal resistance and capacity. The value range of topology height and width is set between 1 and 2. The range values of allowable efficiency and domain are 0.1-0.02 and 3-0 respectively. In the clustering process, the number of clusters was set as 2-5 groups, and the clustering was conducted for four times according to the number of cluster groups. Table 3 presents the results of clustering. The clustering process is run on statistica12.[21]

TABLE 1 Information of resistance measuring device

Items	Information
Model number	YR1035+ Battery resistance measuring device
Voltage measuring range	0 V-100 V DC
Resistance measuring range	0.01 mΩ-200 Ω
Normal operating temperature range	10°C-40°C
Manufacturing company	Jinan Yaorui Electronics

3.1.3 | New battery pack assembling

Twelve similar batteries are chosen according to the results of the clustering performance to synthesize a new battery. From Table 1, there are 6 groups found to meet the battery number more than or equal to 12 that are group 1, 2 in first clustering, group 1, 2 in second clustering, group 3, 3 in third clustering, group 4 in fourth clustering. It seems that 12 out of these six groups can be picked. However, the operation process of the SOM neural network is to cluster the test objects according to their similarity. The more the number of groups is, the greater the similarity between the objects in the results and the smaller the difference will be gotten. Therefore, the group with the best similarity among the above six groups is the fourth group in fourth clustering (Table 4). Numbers for 17, 19, 21, 26, 32, 33, 36, 40, 41, 42, 43, 44 are chosen as a group, and another 12 batteries are randomly selected for another group. The battery packs with 12 individual cells need to be molded before experiment. To ensure three battery packs as consistent as possible, the newly assembled battery pack simulates the steps of the battery assembly by the manufacturer. The battery connects with a charge and discharge protection plate, a plastic bracket. And the battery connection is welded with Nickel plates. The assembly process is shown in Figure 5.

When battery assembled, the undisassembled battery pack E above is marked pack 1, the battery pack assembled randomly is marked pack 2 and the battery pack with high similarity carefully screened is marked pack 3. The experimental is performed in open environment and the ambient temperature is 298.15 K. The parameters to be considered in the comparative experimental of battery performance are temperature and capacity. Therefore, six temperature sensors were installed in each of the

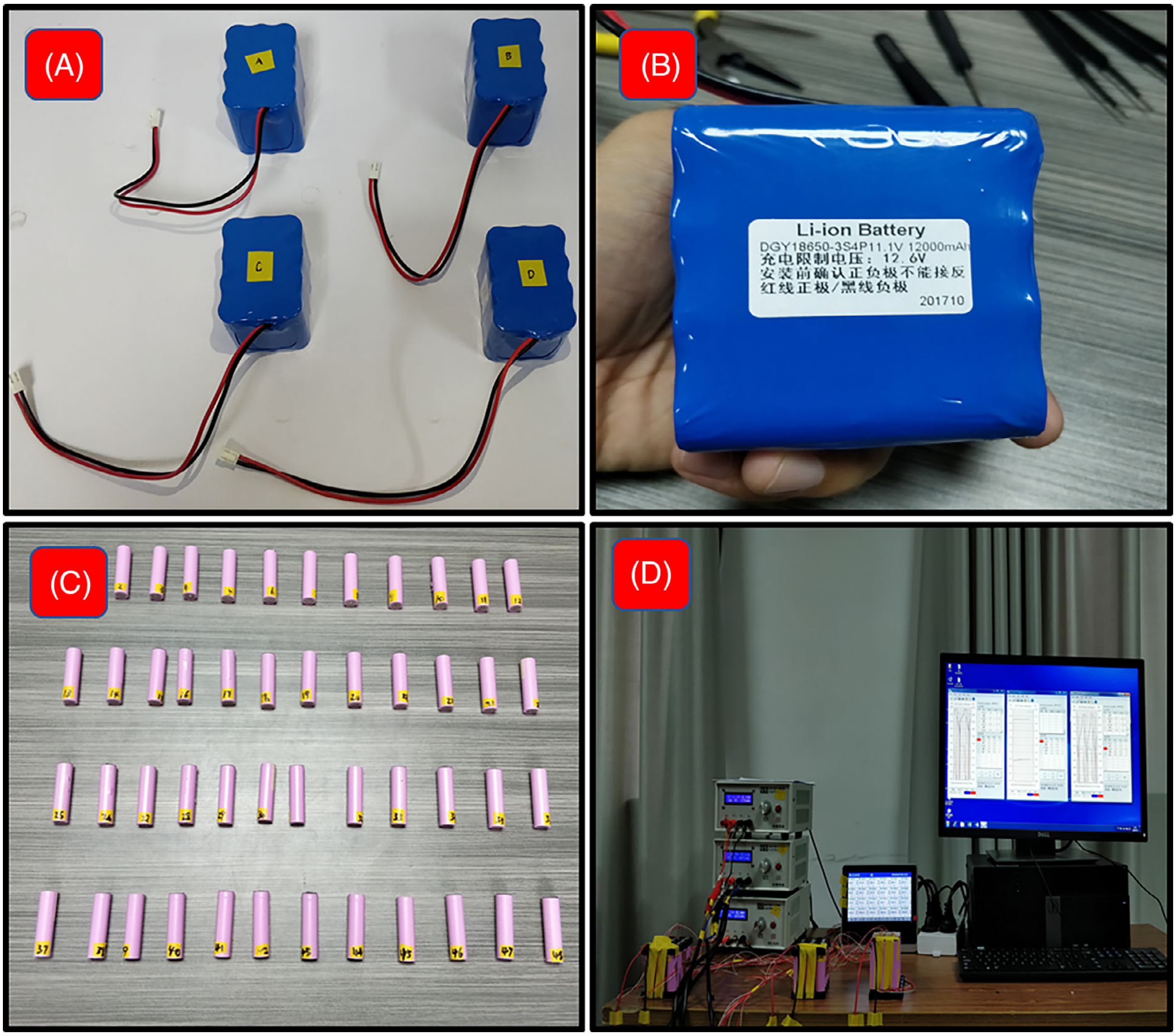

FIGURE 4 Process of battery disassemble [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Testing procedure of clustering experiment

Steps	State	Value	Cut-off voltage
1	Constant current and constant voltage charge	1.3 A 4.2 V	4.2 V
2	Rest	30 min	
3	Constant current discharge	1.3 A	2.75 V
4	Rest	30 min	

Note: Maximum safety Voltage: 4.3 V; minimum safety Voltage: 2.65 V.

TABLE 3 Average battery pack capacity test experiment results

Parameters	Pack 1	Pack 2	Pack 3
Maximum value of capacity (Ah)	10.79	10.61	10.79
Minimum value of capacity (Ah)	10.7	10.28	10.71
Average value of capacity (Ah)	10.74	10.53	10.744
MSE	0.0008	0.0049	0.0005

three battery packs to record temperature data. In the comparison experiment, three battery packs are connected into the battery tester at the same time for 20 charging and discharging cycles. During this process, the battery tester would automatically record the capacity data.

4 | EXPERIMENTAL RESULT AND DISCUSSION

In Figure 6, it is obvious that the performance of pack 2 is worse than pack 1 and pack 3, and there is no much differences in packs 1 and 3. In Table 3, it can see that

TABLE 4 Results of clustering

Clustering	Classification group	LIB number
1st cluster	1	1,2,3,4,8,10,11,12,13,15,25,27,29,30,31
	2	16,17,19,21,26,28,32,33,34,36,38,39,40,41,42,43,44,45
2nd cluster	1	1,2,3,4,8,10,11,12,13,15,25,27,29,30,31
	2	17,19,21,26,32,33,36,39,40,41,42,43,44
	3	16,28,34,38,45
3rd cluster	1	1,2,3,4,8,11,12
	2	10,13,15,25,27,29,30,31
	3	16,28,34,38,39,45
	4	17,19,21,26,32,33,36,40,41,42,43,44
4th cluster	1	10,25,27,29,30,31
	2	2,4,11,12,13,15
	3	1,3,8
	4	17,19,21,26,32,33,36,40,41,42,43,44
	5	16,28,34,38,39,45

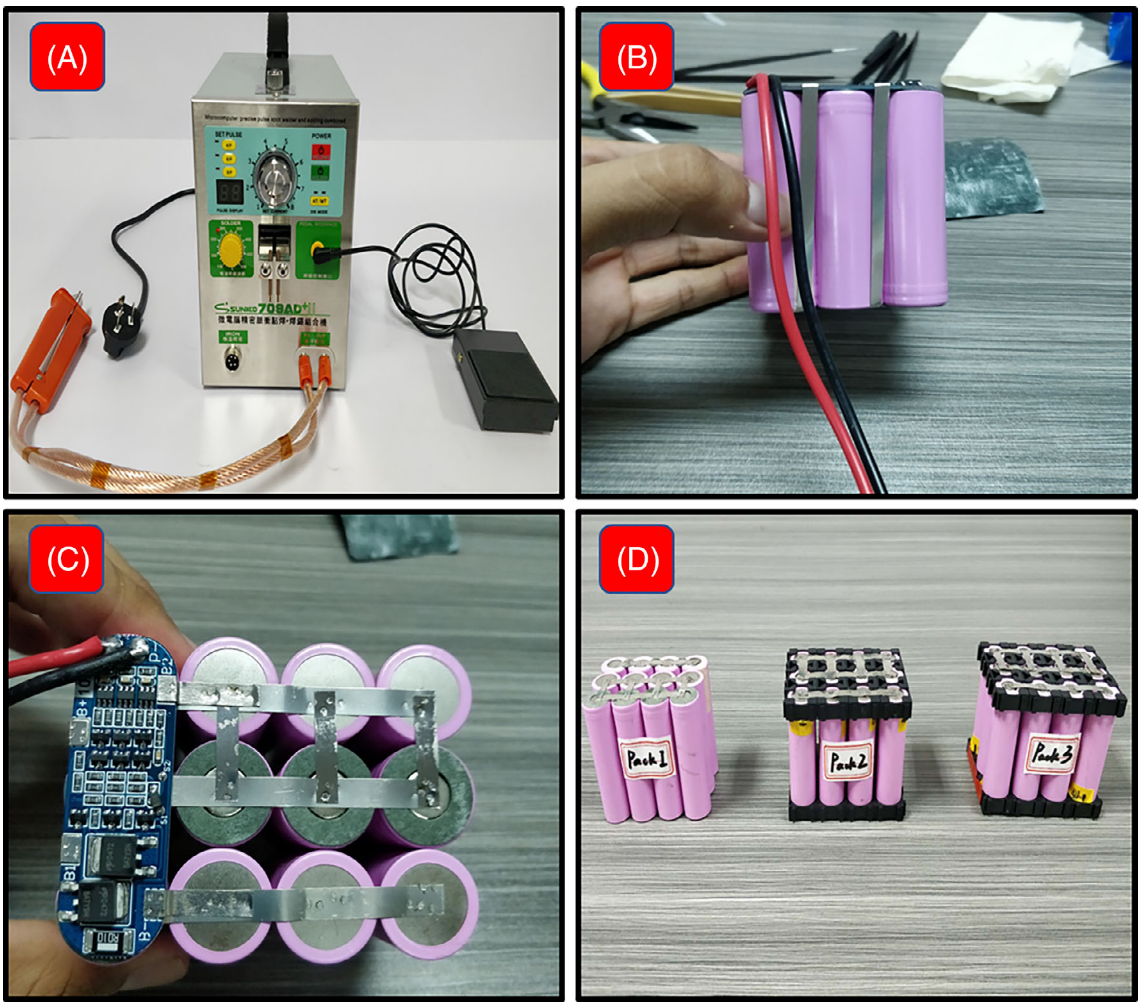

FIGURE 5 New battery pack assembling process [Colour figure can be viewed at wileyonlinelibrary.com]

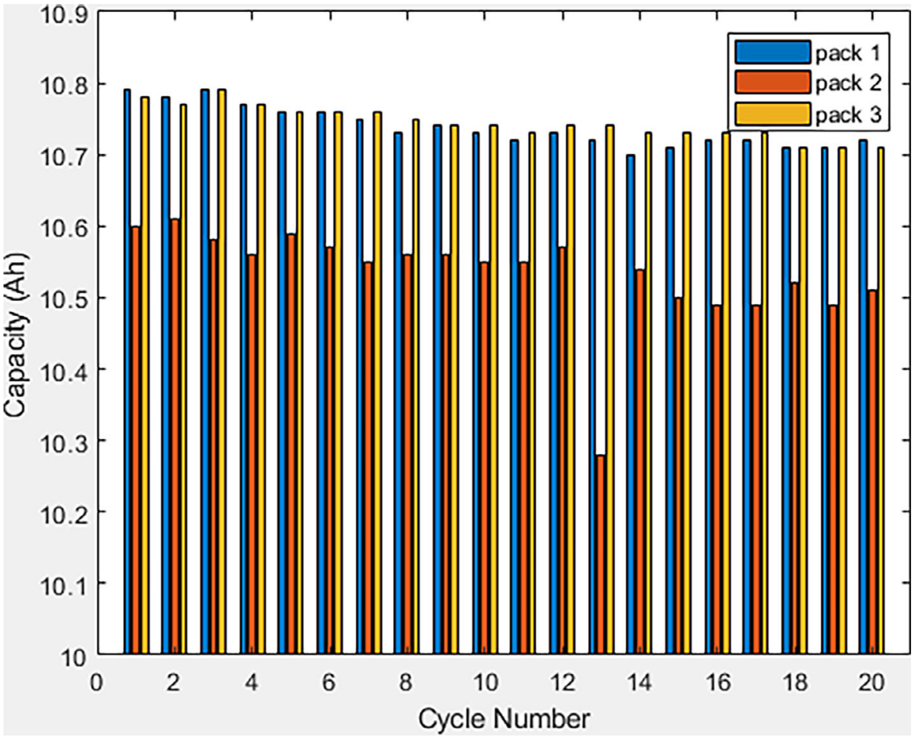

FIGURE 6 Battery pack capacity experimental results [Colour figure can be viewed at wileyonlinelibrary.com]

the performance of pack 3 is the best, pack 2 is the second best, and pack1 is the worst only considering capacity parameters. Low capacity means limited electric energy. Higher temperature means accelerated aging and more safety issues. The maximum, minimum, and average capacity of the pack 2 is smaller than that of the pack 1. Above all, mean squared error of pack 3 is the smallest which is a little lower than that of pack 1. This is because manufacturers simply screen the batteries before assembling them, which makes the original battery pack better than the one that is assembled randomly.

The maximum capacity of pack 3 is the same as that of pack 1, but its minimum capacity and average capacity are slightly higher than that of pack 1, which indicates that clustering analysis has a significant contribution to improving the overall performance of battery packs.

Two hundred sampling points are shown in Figure 7. Temperature and capacity are simultaneously recording while charging and discharging process. At the beginning of the cycle, the battery pack temperature increases gradually from normal temperature. And after several cycles it reaches the temperature change state when the battery in actual work. Thus, the data of first three cycles are removed for its abnormality. As mentioned above, the weakest cell limits capacity of the whole pack. However, charging and discharging time depends on its capacity which explains the difference of cycle time of three packs. From Figure 8, result shows that temperature of pack 3 is much lower than the other two packs especially maximal average temperature. Temperature of pack 1 is the highest which reveals the disadvantages of manufacturer's screening. There are three main sources of temperature difference:

1. the heat release of different single batteries in the battery pack and the inside heat dissipation effect of battery pack are different.
2. the current near battery pack charge and discharge protection board is slightly larger than that in any other places, so the heat release here is the highest.
3. the heat release of the battery is also different in different stages of its charging and discharging process.

To comprehensively compare the temperature performance differences of the three battery packs, obviously, it can be seen that pack 3 has the smallest temperature change and the lowest peak temperature during the whole process, and its performance is better than the other two battery packs. This also shows that the overall performance of the battery pack analyzed by clustering method can be improved.

5 | CONCLUSIONS

This paper focuses on addressing the problem of inconsistency of cells in the LIB packs. A machine learning approach is applied to the LIB parameters (internal resistance, capacity and voltage). Based on clustering analysis results, LIBs perform similar are assembled together to

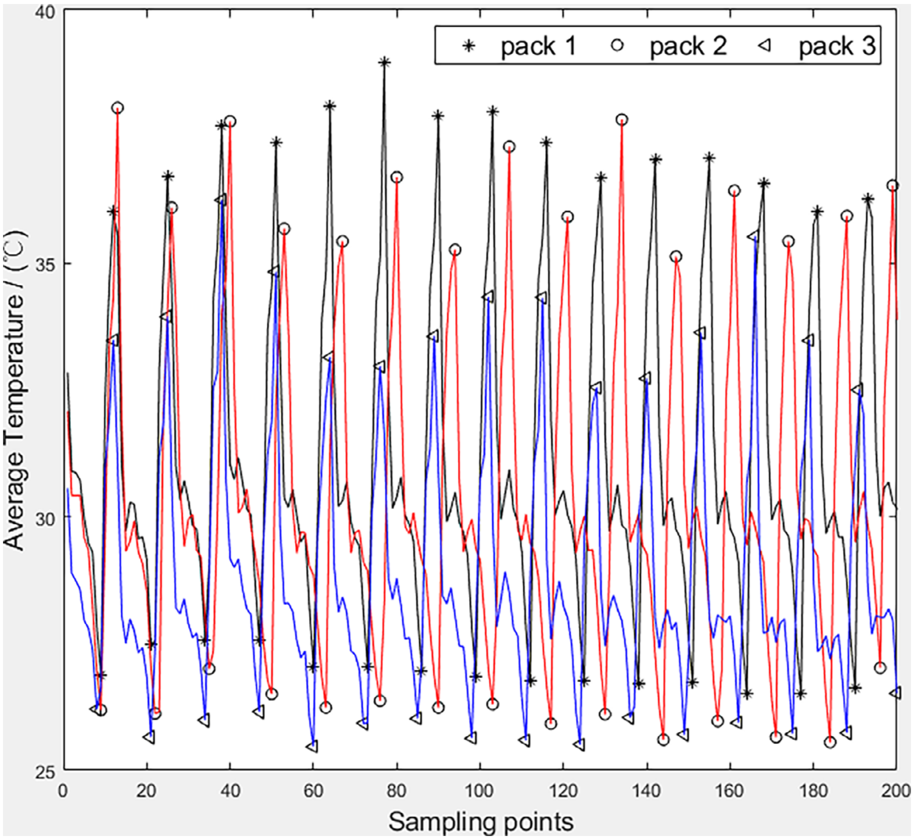

FIGURE 7 Comparison of average temperature in packs [Colour figure can be viewed at wileyonlinelibrary.com]

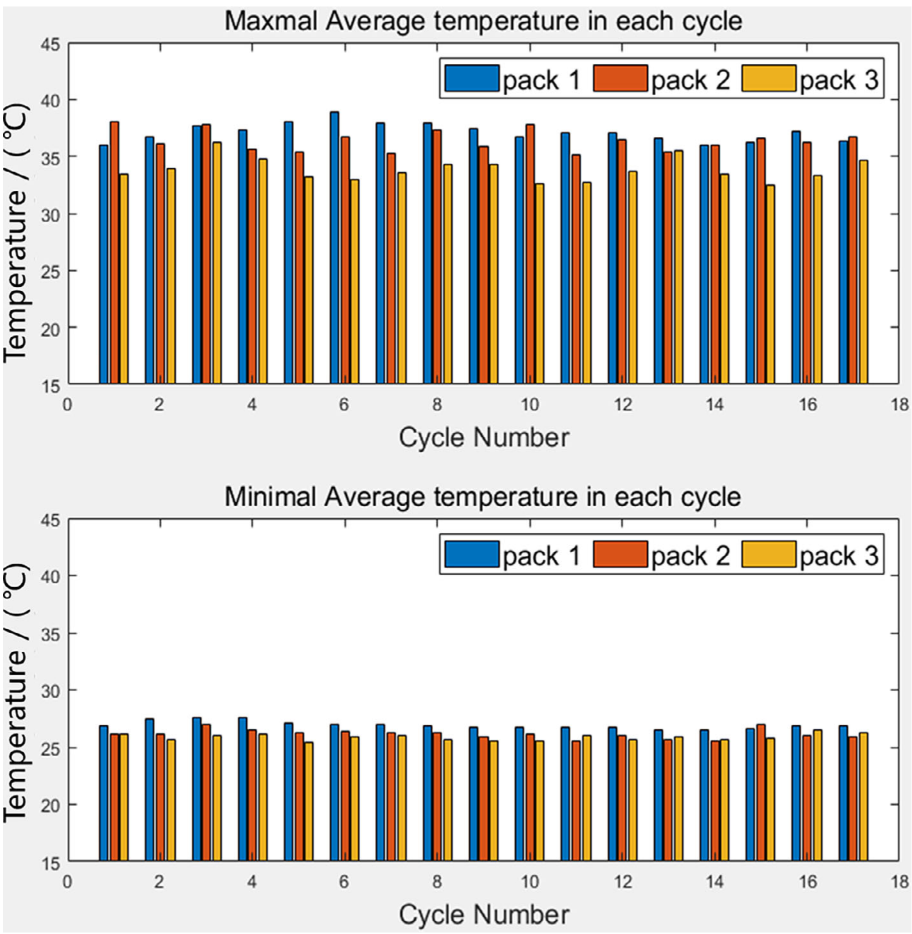

FIGURE 8 Maximal and minimal average temperature in packs [Colour figure can be viewed at wileyonlinelibrary.com]

form the new battery pack. Experiments are then performed to validate the numerical results.

According to the experimental validation of machine learning method, the following conclusions are drawn in this paper:

1. The battery pack capacity can be improved to a certain extent after through clustering analysis. The capacity of clustered battery pack increased 1.9% compared with brand-new pack.
2. Internal temperature difference between single batteries exists, the maximum temperature difference reaches 7°C.
3. The assembled battery pack after screening has a higher consistency of internal temperature distribution. Peak temperature is lower by 4°C-5°C than general battery pack and fluctuation of temperature also reduces 2.6°C.

6 | FUTURE RESEARCH DIRECTIONS

6.1 | Automatic LIB recycling system development

The challenge for battery recycling is a multidisciplinary and multi-objective comprehensive problem. The current recycling technology is not mature enough and lacks a systematic recycling framework. Therefore, a multi-level and multi-objective comprehensive interdisciplinary solution for LIB recycling need to be proposed. Applying artificial intelligence technology to solve the difficult problems in the field of recycling and providing technology for the recycling as well as secondary utilization of LIBs is necessary. In addition, a big data platform and intelligent visualization platform need to be developed for intelligent disassembly of battery packs, condition monitoring of LIBs, and remaining life prediction.

6.2 | Hybrid energy storage system design

In order to improve the utilization of energy system, realize energy storage, scheduling, secondary utilization, etc., it is necessary to develop intelligent hybrid energy storage system. This system can be applied to typical household power supply, and also can provide power for island or remote areas (such as microgrid). Through the application of energy storage system technology, the system can also provide energy compensation for common large-scale energy demand system to reduce economic costs and improve environmental benefits. The key technology of developing hybrid energy storage system is energy storage, transportation and intelligent management. Therefore, the development of intelligent energy management system is a very important research direction. In addition, the stability of the system is also one of the key issues worth studying.

6.3 | Renewable energy application on shipping industry

With the rise of renewable energy technology, the application of renewable energy sources such as wind and solar energy to the shipping industry has been gradually receiving attention from researchers and governments. Because the zero-emission feature of renewable energy can significantly reduce the carbon emissions of shipping. However, a major drawback of limiting the application of renewable energy is that its energy supply is extremely susceptible to the environment (such as weather), and the total amount of renewable energy that can be actually absorbed by the power grid is also unknown. Therefore, relevant techniques need to be further studied.

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