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A Cell Screening Algorithm Integrating Genetic and Numerical Differentiation

Zhen Wu*, **Feijing Fu, Yirga Eyasu Tenawerk, Weize Quan, Wanwen Wu**

College of Information Engineering, Nanchang Hangkong University, Fenghenan Road, No. 696, Nanchang 330063, Jiangxi Province, China

***Corresponding author:** Zhen Wu, 1067977498@qq.com

Abstract: The consistency of the cell has a significant impact on battery capacity, endurance, overall performance, safety, and service life extension. However, it is challenging to identify cells with high consistency and no loss of battery energy. This paper presents a cell screening algorithm that integrates genetic and numerical differentiation techniques. Initially, a mathematical model for battery consistency is established, and a multi-step charging strategy is proposed to satisfy the demands of fast charging technology. Subsequently, the genetic algorithm simulates biological evolution to efficiently search for superior cell combinations within a short time while evaluating capacity, voltage consistency, and charge/discharge efficiency. Finally, through experimental validation and comparative analysis with similar algorithms, our proposed method demonstrates notable advantages in terms of both search efficiency and performance.

Keywords: Genetic differentiation method; Battery consistency; Voltage fluctuation; Fast charging technology; Battery cell screening

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1. Introduction

In the context of increasing attention to climate change and environmental degradation, Battery Electric Vehicles or Pure Electric Vehicles (BEV or EV) have become an alternative to traditional Internal Combustion Engine (ICE) vehicles, and lithium batteries open a new era [1]. They are a promising energy storage device for electric vehicles and renewable energy systems. Compared with traditional lead acid, nickel-iron, and nickel metal hydride batteries, advanced Lithium-Ion Batteries (LIBs) are considered the most promising electrochemical energy storage devices [2,3]. However, current chargers typically require over eight hours to add 200 miles of range to electric vehicles, making them unsuitable for highway journeys and extended trips. Therefore, there is an urgent need to improve the charging speed of on-board battery chargers, so that they can rapidly improve the charging capacity of batteries [4].

In practical applications, to meet the requirements of power and energy, the battery is usually connected in series to form a high-voltage battery pack, and the inconsistency between the cells is the key factor affecting the overall performance of the battery pack [5]. The cell is the cornerstone of the whole battery system, but due to some uncontrollable reasons, the actual voltage and State of Charge (SOC) of the battery in the same battery pack may vary, and this inconsistency of the battery will damage the durability and safety of the battery pack [6]. Related studies show that the temperature of the power battery pack and its consistent state are important indicators of thermal runaway risk. When the battery consistency is poor, there is likely to be a thermal failure or high cell temperature in the battery pack, which can easily lead to thermal runaway [7,8]. The battery inconsistency usually comes from the battery manufacturing process, and this inconsistency may be further expanded during the operation of the battery system [9]. Although this difference is small from a macro perspective, it causes significant changes during battery operation. Therefore, in the process of battery manufacturing, the selection of cells is a crucial link. The selection of cells will affect the performance and safety of electronic products, and the selection of high-consistency and small voltage fluctuation cells is crucial to ensure the best performance, service life, and safety of these electronic products.

In the existing literature, there has been a variety of cell screening algorithms that have been widely discussed. Among them, the machine learning algorithm gradually emerged, providing a new perspective for cell selection, commonly used machine learning-based battery cell selection methods generally include the K-means algorithm, fuzzy C-means algorithm, and Kohonen network method [10–16]. Recently, the Particle Swarm Optimization (PSO) algorithm has also shown its potential in cell selection [17]. In addition, Genetic Algorithm (GA) is also applied in the preferred process of lithium-ion batteries for electric vehicles. By integrating multiple parameters such as capacity, internal resistance, and cost, they explore the optimal battery combination with the GA algorithm. Compared with the conventional method, the dual optimization of cost reduction and performance improvement is achieved [18]. Moreover, the numerical differential method can also be used for the screening of battery cells. Its principle is to use some discrete points of the original function to construct a specific function to approximate the original function, and then take the derivative of the constructor as the approximate derivative of the original function [19]. This paper presents a novel integration of the Differential Genetic (DG) algorithm and numerical algorithm, based on the widely used cell screening method. Simultaneously constructing an optimized cell screening model for the DG algorithm, this approach efficiently and accurately screens high-consistency and low-voltage fluctuation cell combinations to address the challenges related to charging efficiency and stability in new energy automotive batteries.

2. Problem analysis

In order to ensure the high efficiency and accuracy of the cell screening process, appropriate screening strategies must be adopted. However, the task of directly screening the cell is particularly complicated. From the classical mathematical perspective, the calculation screens 24 suitable cells from 76 cells, and its calculation amount is undoubtedly huge. Specifically, the combined formula in combinatorial mathematics is used to perform the calculation. The combination number $C(n,k)$ is defined as the total number of methods for screening *k* elements from *n* elements, and the formula is:

$$C(n,k)=\frac{n!}{k!(n-k)!} \tag{1}$$

Where $n!$ is the factorial *n*, i.e. $n\times(n-1)\times\ldots\times 1$, in this problem, we propose, *n* = 76, *k* = 24. *C*(76,24) can therefore be expressed as follows:

$$C(76,24)=\frac{76!}{24!(76-24)!}=\frac{76!}{24!52!}=\frac{76\times 75\times 74\times\ldots\times 53}{24\times 23\times 22\times\ldots\times 1}=75287520 \tag{2}$$

After the above calculation, up to 75,287,520 different combinations were screened from 76 samples, a number that intuitively reveals the great challenges and complexity of the cell screening task. Therefore, the traditional mathematical method is inadequate when dealing with such a large cell scale, which is time-consuming and inefficient. The accuracy and efficiency are difficult to reach the standard in the face of the urgent social demand for high-performance batteries.

3. Model construction

3.1. Optimized cell screening model

To evaluate the impact of cell inconsistency on the overall performance of the battery pack, it is necessary to construct an effective battery pack consistency model, which can describe both the statistical characteristics of the battery consistency parameters and the correlation between the parameters [20]. Therefore, based on the above battery consistency problem, this experiment builds an optimized cell screening model. The model aims to serve for physical experiments. Through the DG algorithm proposed in this paper, the best-performing 24 cells were selected from 76 ternary lithium-ion cells to form a cell combination, improving the stability of the battery.

3.2. Multi-step charging strategy

This experiment designs a multi-step constant current charging strategy suitable for the optimized cell screening model to test the ternary lithium-ion cells. In most experiments, the constant current charging method is the preferred charging strategy because it provides accurate and practical information on battery performance, in line with the experimental objectives and requirements [21]. To satisfy the demand for fast charging, this experiment improved the constant current charging process by adopting a multi-step constant current charging strategy.

The specific steps are as follows: Before cell charging, all the cell samples are set to an initial voltage of 3.6 V for charging. Then, enter three stages of the rapid charging process, a constant current of 57 A for 200 s, then a current of 44 A for 95 s for charging and monitoring the temperature to prevent overheating. At 295 s, the qualified cells are screened by checking the voltage difference. After that, the current is further reduced to 33 A until the cell voltage reaches the cut-off voltage of 4.35 V, which avoids voltage overshooting. Finally, after the cell reaches 4.35 V, the system automatically switches to the slow charging mode of low current until the cell is filled, effectively preventing the damage caused by overcharging the cell.

3.3. Voltage difference

The optimized cell screening model requires ensuring that the battery pack shows the highest consistency possible during the rapid charging process while ensuring that the overall voltage fluctuation is as small as possible. In the experimental process of fast charging, the voltage detection compared to capacity is real-time, fast, and easy to implement and is well suited for assessment research [22]. Therefore, this experiment needs to calculate the voltage of the cell at each time point and screen the cell with high consistency by comparing the voltage difference of each cell at a certain time point. After calculating the voltage difference of each cell at the same specific time, the consistency level of the whole battery pack can be quantified.

The calculation method of voltage differential, V_d pressure of the cell is first to calculate a voltage measurement sequence, $V = [V_1, V_2, \ldots, V_n]$, according to the test data, n is the total test time of the cell. The model is mainly based on the optimization of the cell screening model using a multi-step constant current charging strategy of three obvious voltage drops at the end of the stage (200 s, 295 s, and cell reaches the off voltage) violent voltage fluctuations to calculate the voltage difference, in the three moments cell will appear a voltage maximum recorded as V_t^{max}. At the same time, a minimum voltage value is recorded as V_t^{min}, so the voltage difference of the cell V_d is calculated as follows:

$$V_d = V_t^{\max} - V_t^{\min} \tag{3}$$

The V_t^{max} represents the maximum voltage value of the cell at the time t, and the V_t^{min} represents the minimum voltage value of the cell at the time t, calculate the voltage difference V_d of the moment between the maximum and minimum voltage values, at the end of the seconds fast charging period, the optimized cell selection model will control the voltage difference of the cell within a preset threshold range, and screen the battery combination meeting the conditions.

3.4. Voltage fluctuation

The calculation of voltage fluctuation is the core part of the optimized cell screening model. Choosing a cell with small voltage fluctuation can reduce the negative voltage effect and improve the performance of operating efficiency [23]. Specifically, the numerical differential method is used to calculate the voltage fluctuations. The first task is to calculate the voltage change rate per second of each cell, the calculation formula is:

$$V_f = \left|V_{i+1} - V_i\right| \tag{4}$$

The V_f represents the voltage rate of change per second of the cell, the V_i represents the voltage value at the time i, and the V_{i+1} represents the voltage value at the time $i+1$. All voltage change rates are then added up to obtain the total value of the voltage change rates $\sum_{i=1}^{n-1} V_d$ in this voltage curve can be expressed as:

$$\sum_{i=1}^{n-1} V_d = \sum_{i=1}^{n-1} \left|V_{i+1} - V_i\right| \tag{5}$$

Next, the total charging time T needs to be calculated. In the actual experiment, because the cell test time has been obtained, the start and end time of each cell charging has been determined, so that T can be accurately expressed as:

$$T = t_n - t_1 \tag{6}$$

Where, t_n is the n seconds which is the end of the fast-charging stage, and t_1 seconds is the time when the charging begins. Divide the cumulative voltage difference value $\sum_{i=1}^{n-1} V_d$ by the total time T to get the average voltage and fluctuation value. Therefore, the mathematical formula for calculating the voltage fluctuation value ΔU of the whole curve can be summarized as follows:

$$\Delta U = \frac{\sum_{i=1}^{n-1} V_d}{T} \tag{7}$$

The calculation formula of the ΔU can be further expressed as follows:

$$\Delta U = \frac{\sum_{i=1}^{n-1} \left|V_{i+1} - V_i\right|}{t_n - t_1} \tag{8}$$

This formula briefly describes how to calculate a series of voltage measurements to obtain the average voltage fluctuation amplitude per second at the same interval of data sampling, and finally get the overall voltage fluctuation value of each cell.

4. Algorithm description

4.1. DG algorithm

To meet the challenges of efficient cell screening in the rapid charging technology of new energy vehicle batteries, a DG cell optimization algorithm is proposed in this study, which combines the global search advantage of the genetic algorithm with the accurate evaluation ability of the numerical difference method [24–27]. Specifically, the DG algorithm aims to screen out cell combinations with high consistency and low voltage fluctuations, and the DG algorithm can exploit the advantages of genetic algorithms, including its parallel processing power and a broad global search range. It can quickly traverse the space and explore potential high-quality solutions. At the same time, the gradient information of the function is accurately calculated by the numerical differentiation method to provide detailed performance feedback for each step of the search. This not only significantly accelerates the convergence speed of the optimization process, but also improves the quality of the obtained cell combination scheme, and greatly reduces the time required to screen a required cell combination to improve the overall consistency and stability of the battery.

4.2. Algorithmic pseudo-code

According to the above description of the DG algorithm, to understand the core execution logic of the DG algorithm more deeply, this paper summarizes the DG algorithm pseudo-code as shown below.

DG algorithm

Import:

Cell sample set: cells_total, the selected number of cells: cells_sel, cell voltage difference threshold: v_threshold, critical test moment of voltage difference: timing, Last second of the fast-charging phase: endtime.

Output:

The file name list: unique_best_individual.

1. foreach cells_total, numbered for each cell and recorded at cells_number.
2. foreach cells_number

    while time < endtime

        time = timing

            If the cell has data at the time

                The voltage difference voltage_difference of the cell is calculated using the formula $V_d = V_t^{\max} - V_t^{\min}$.

                if voltage_difference > v_threshold in timing

                    Excluding the cell, and break

                else add the cell number to the preferred cell list cells_better, calculates the voltage fluctuation value voltage_diffs of the cell using the numerical differential formula $\Delta U = \frac{\sum_{i=1}^{n-1} |V_{i+1} - V_i|}{t_n - t_1}$ and returns the value, and break.

    Else time = time + 1

3. foreach cells_better performed the genetic algorithm

    Initialize a population of 24-cell individuals and perform iterative genetic operations based on voltage fluctuation values (voltage_diffs) over multiple generations. These operations, including selection, crossover, and variation, refine the population's fitness values at each generation's end. After completing the iterations, record the individual with the highest fitness level as the optimal combination of cells in the 'unique_best_individual' list.

4. Return unique_best_individual.

5. Experiment

5.1. Data analysis

This experiment is based on the optimized cell screening model design of a multi-step constant current charging strategy, for the 76 ternary lithium-ion battery samples through the physical experiment equipment charge test and obtain the data of the cell. To better screen the cell, firstly, need to analyze the cell voltage data. **Figure 1** shows the 76-cell charging voltage curve.

The voltage curve data in **Figure 1** only goes up to 700 seconds as this experiment focuses on the cell's performance during fast charging. Each cell is represented by a different color, revealing its charging characteristics. The red, green, and yellow dotted lines in **Figure 1** mark the three stages of the charging strategy at 200 s, 295 s, and 400 s respectively. From **Figure 1**, it can be observed that the cell's voltage rises rapidly initially due to the higher current used by the test device to speed up charging and restore battery capacity quickly. When the voltage reaches around 4.35 V (the cut-off voltage set by the multi-step charging strategy), usually after about 400 s, there is a brief drop in voltage forming a platform which indicates the end of the rapid charging phase. Subsequently, the system automatically switches to a slow charging phase with significantly reduced and stable current while maintaining relatively stable voltage levels to prevent overcharging and overheating while ensuring full charge. The discharge voltage curves of 76 ternary lithium-ion cells are shown in **Figure 2**.

According to **Figure 2**, the discharge voltage curve turns from falling to rising in the period of 6000 s to 8000 s, marking the end of the discharge process of the cell. Fast charging technology can complete the charging of the cell in a short time. To prolong the battery life, it usually reduces the discharge rate of the cell, so the discharge time is longer than the charging time. Next, at the critical test moment, 295 s, the cell data, to more intuitively analyze the voltage difference change of the cell at this time, as shown in **Figure 3**.

The X axis in **Figure 3** represents the time point, the Y axis represents the voltage difference, and the Z axis represents the file index of the cell from 1 to 76, where each data point represents the voltage difference of the cell at the end of the second's fast charge phase. If there is no data or large voltage fluctuation at 295 s, the end time of the seconds' fast charging phase is delayed. In this case, the voltage difference at 296 s is screened in this experiment to represent the end of the seconds fast charging phase of the cell. The voltage difference of the cell in **Figure 3** is mainly distributed in the range of 0023 V to 003 V, and there is a difference of 0007 V in the range. Therefore, it can be determined that the threshold value V_d of the voltage difference is 0026 V, that is, the voltage difference is less than 0026 V at the end of the period is good. Finally, 40 cells meeting the voltage difference threshold requirement of 0026 V are screened from the 76 cells. The voltage fluctuation value curves of the 40 candidate cells meeting the voltage difference threshold requirements are shown in **Figure 4**.

In **Figure 4**, each data point on the voltage fluctuation value curve marks the corresponding cell number. **Figure 4** directly reflects the overall condition of the 40-voltage fluctuation, but the voltage fluctuation of some cells has large or small overall voltage fluctuation. Therefore, the genetic algorithm to further screens the 40 cells, with the average voltage fluctuation value of 76 cells as the fitness evaluation criterion, screens the cells with relatively small voltage fluctuation.

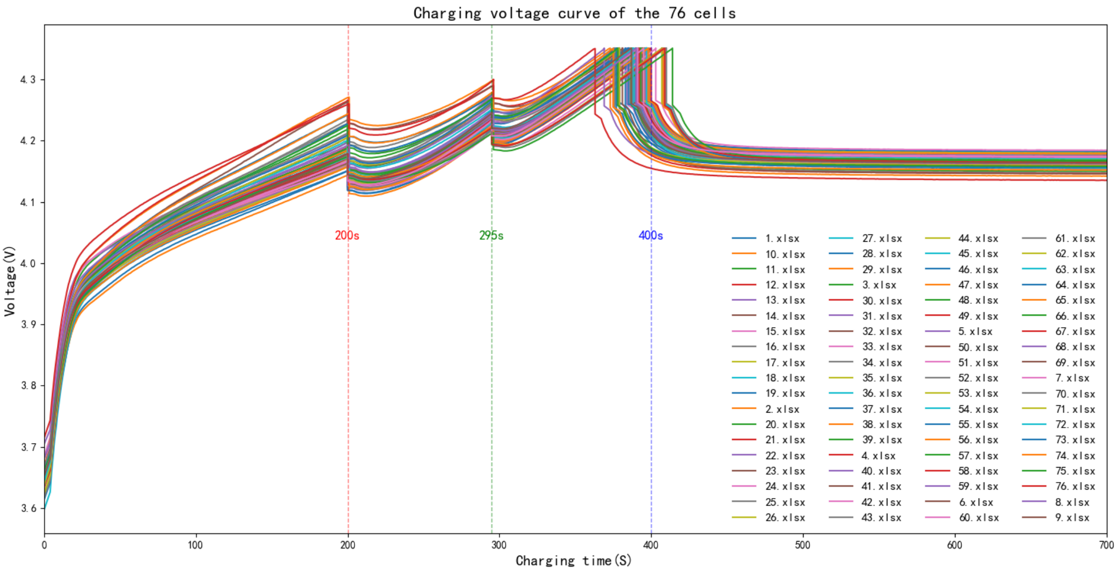

Figure 1. Charging voltage curve diagram of the initial 76 cells

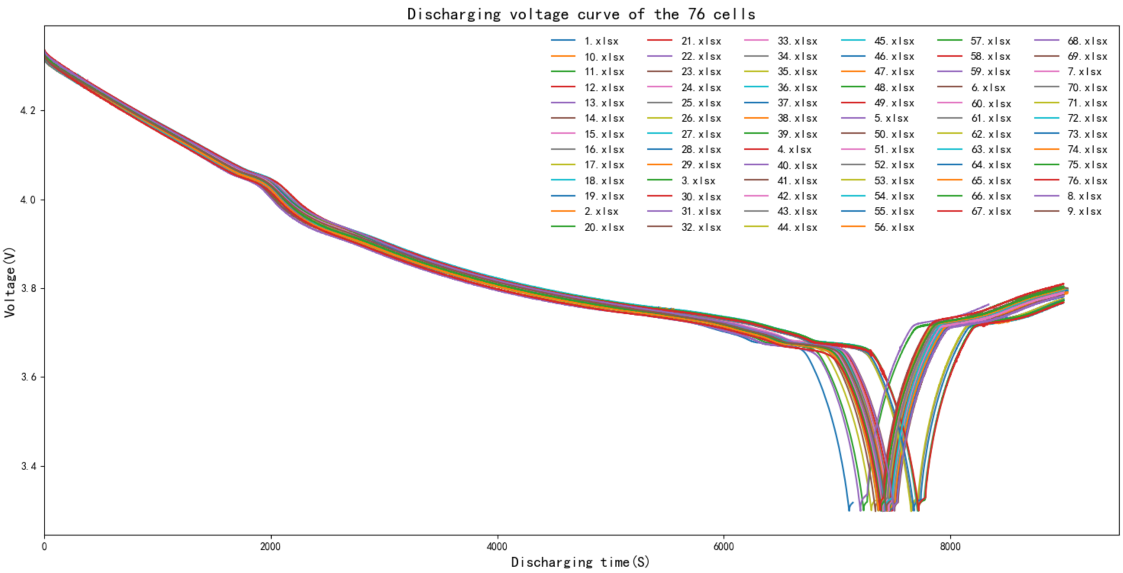

Figure 2. The discharge voltage curve diagram of the initial 76 cells

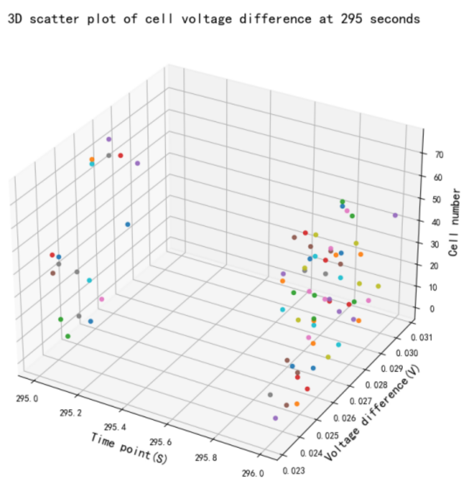

Figure 3. 3D scatter plot of the voltage difference of 76 cells at 295 s

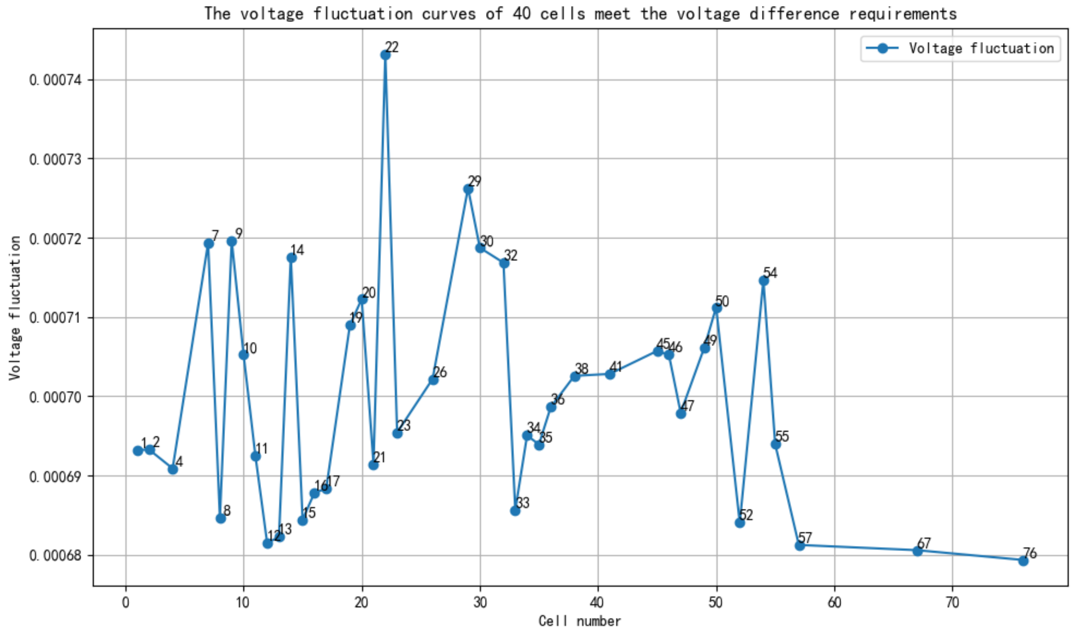

Figure 4. Graph of the voltage fluctuation value of the cell meeting the voltage difference requirements

5.2. Experimental results

The genetic algorithm is used to further screen the cells that meet the voltage difference standard requirements, and the charging voltage curve of the 24 preferred cells is shown in **Figure 5**. Compared with **Figure 1**, it can be observed that the different cells are smaller in the abscissa in **Figure 5** and the voltage curve is more concentrated. Similar differences are presented when comparing the discharge voltage curves of the initial 76 cells in **Figure 6** and **Figure 2**. This indicates that the preferred cells screened by using the DG algorithm can show a more and smaller voltage difference.

The 3D scatter plot of the voltage difference of the preferred cell at 295 s is shown in **Figure 6**. By comparing **Figure 6** and **Figure 3**, there is a finding that the overall voltage difference of the cell combination in **Figure 6** is mainly distributed between 0024 V and 002575 V, with a difference of only 000175 V, which is much less than the 0007 V voltage difference shown in **Figure 3**. This further confirms the superiority of the DG algorithm in screening the cells. The 3D scatter plot of the voltage difference of the preferred cell at 295 s is shown in **Figure 7**.

At the same time, the overall voltage difference of the cell combination in **Figure 7** is mainly distributed between 0024 V and 002575 V, with a difference of only 000175 V, which is much less than the 0007 V voltage difference as shown in **Figure 3**. Then the comparison diagram of the voltage fluctuation values of 40 cells and 24 preferred cells that meet the voltage difference threshold is shown in **Figure 8**.

The yellow line in **Figure 8** represents the 40 cells meeting the voltage difference threshold, and the blue line represents the final screened 24 preferred cells. In **Figure 8**, it can be found that the voltage fluctuation of the preferred cell is in a smaller range, which can prove that the DG algorithm can effectively improve the overall stability of the battery pack.

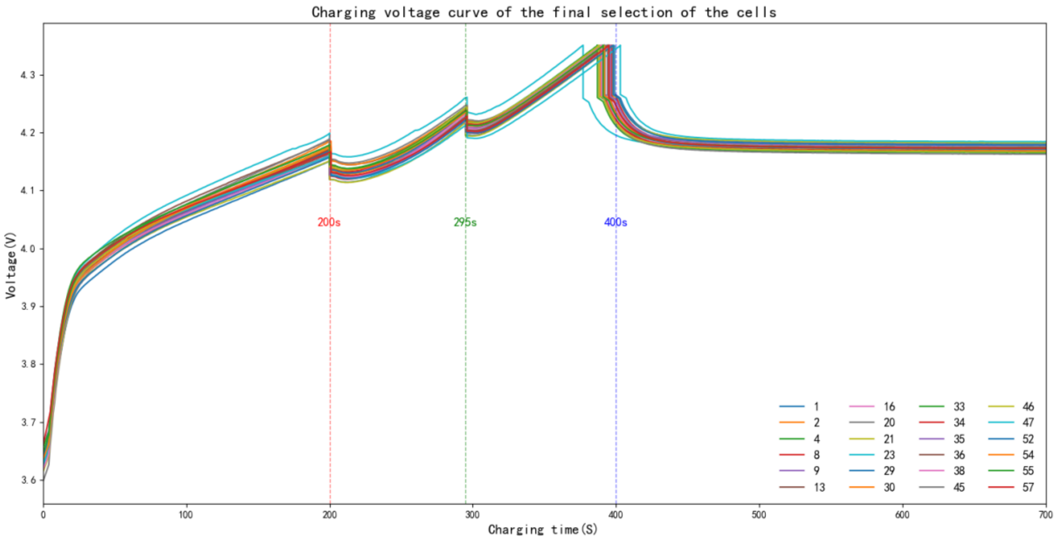

Figure 5. Graph of the final screened cell charging voltage curve

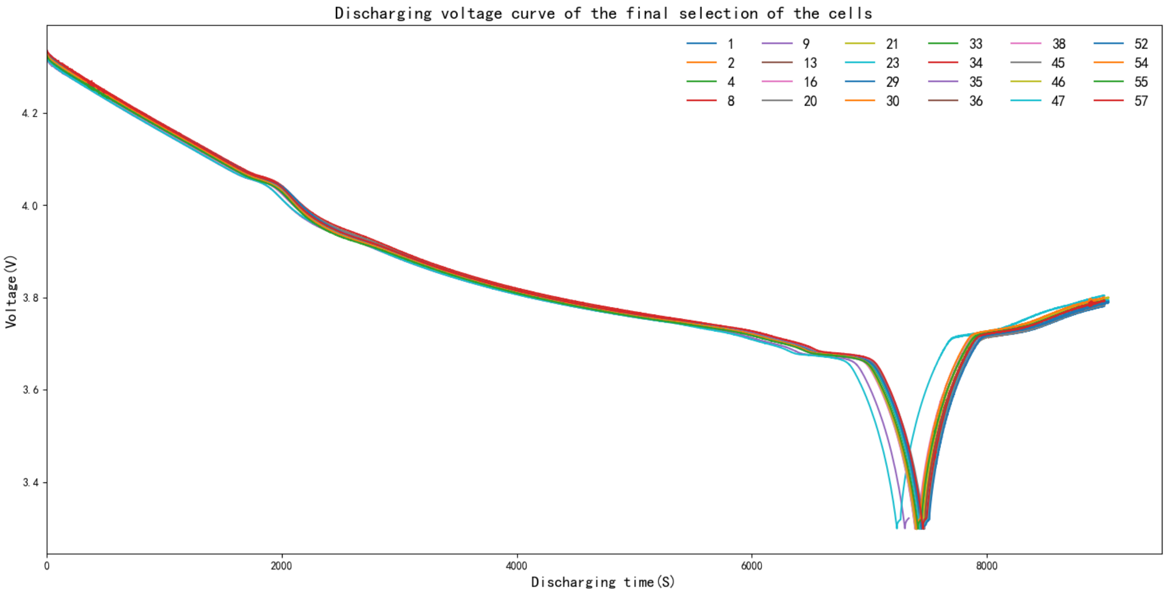

Figure 6. Discharge voltage curve diagram of the final screened cell

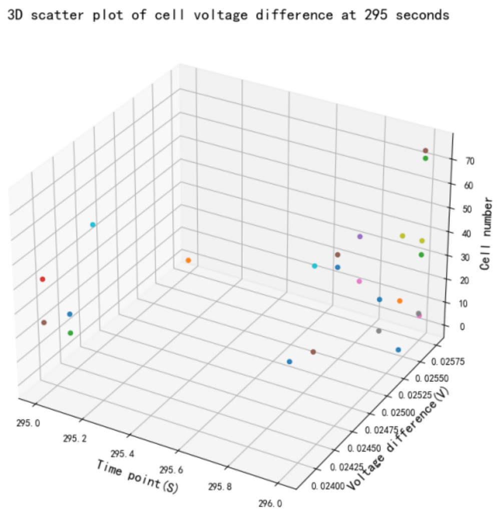

Figure 7. 3D scatter plot of the voltage difference of the final screened cell at 295 s

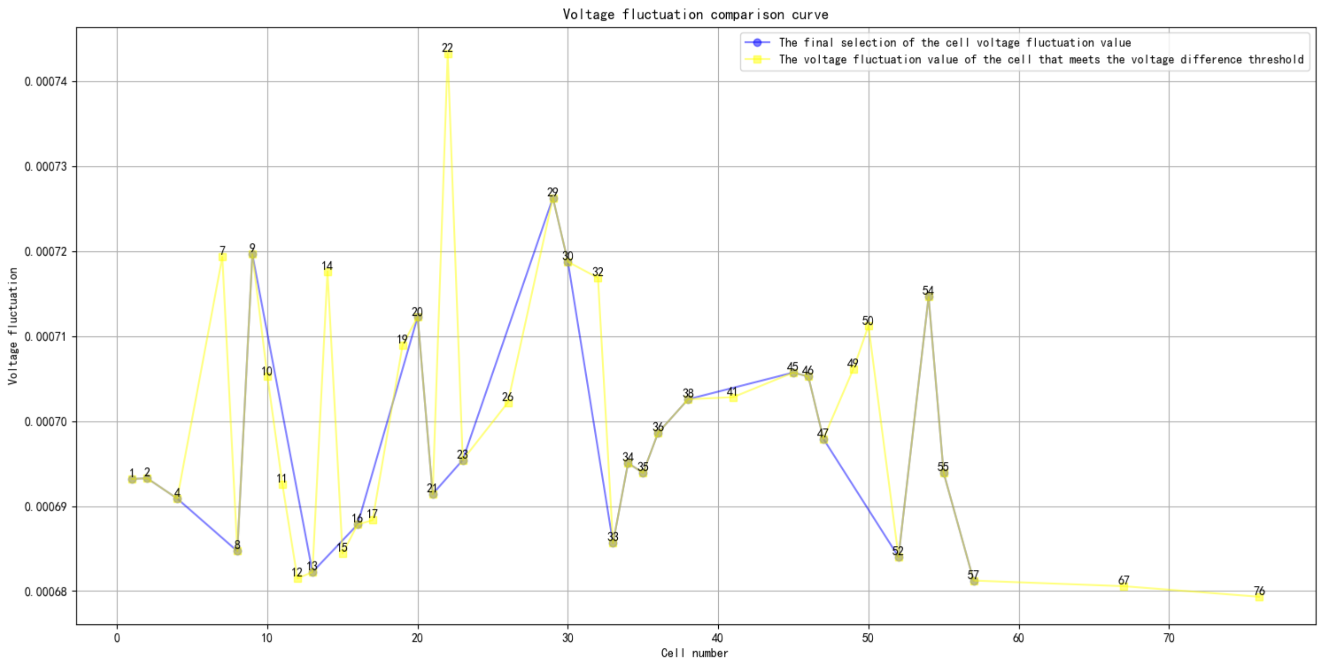

Figure 8. Comparison of the voltage fluctuation values of the two cells

6. Conclusion

In the background of the rapid development of new energy vehicles, how to screen out the cell combination with high consistency and small voltage fluctuation to improve the overall performance of new energy vehicle batteries is facing important challenges. To address this issue, the present study proposes a novel DG algorithm that combines the global search capability of genetic algorithms with the precise evaluation ability of numerical differentiation. Subsequently, an optimized cell screening model is developed to support the DG algorithm. By utilizing this approach, a set of 24 cells exhibiting high performance out of 76 ternary lithium-ion cell samples are screened based on their high consistency and low-voltage volatility, resulting in a combination with superior overall performance. In summary, the DG algorithm not only improves battery performance significantly but also simplifies decision-making, enhances screening efficiency and accuracy, effectively resolves battery consistency issues, and meets consumer demands for faster charging of new energy vehicles. Additionally, the DG algorithm is expected to promote the widespread adoption of new energy technology and sustainable traffic development.

Disclosure statement

The authors declare no conflict of interest.

Author contribution

Writing – abstract: Weize Quan
Writing – body: Zhen Wu
Investigation: Zhen Wu
Analysis – data plot: Wanwen Wu

Figures: Feijing Fu
Literature research: Yirga Eyasu Tenawerk

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