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Altered Artificial Algae Algorithm (AAAA) based Optimized Battery Cell Balancing using T-shaped H-Bridge (THB) Multi Level Converter

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Abstract

Battery cell imbalance remains a major challenge in series-connected lithium-ion battery packs, affecting efficiency, safety, and lifespan. Variations in manufacturing, temperature distribution, and aging lead to unequal states of charge (SOC) among cells, resulting in reduced usable capacity and increased risk of degradation. To address these issues, an optimized battery balancing approach based on an Altered Artificial Algae Algorithm (AAAA) integrated with a T-shaped H-bridge (THB) multilevel converter was presented. The proposed method formulates the balancing problem as an optimization task aimed at minimizing SOC deviation across cells. The AAAA enhances the conventional Artificial Algae Algorithm by incorporating adaptive energy updating, improved exploration–exploitation balance, and mutation-based diversity mechanisms, enabling faster convergence and avoidance of local minima. The THB multilevel converter facilitates efficient energy redistribution with reduced switching losses and improved voltage control. A simulation model was developed in MATLAB/Simulink to evaluate system performance under varying imbalance conditions. Results demonstrate significant improvements in balancing speed, energy efficiency, and SOC uniformity compared to passive methods and conventional optimization techniques such as GA and standard AAA. The proposed approach achieves faster convergence, reduced power loss, and stable operation under dynamic conditions. The integration of advanced optimization with an efficient converter topology provides a robust solution for modern battery management systems, particularly in electric vehicles and renewable energy applications.

1. Introduction

The imbalance of the battery cells in series-connected lithium-ion battery packs was found to be a severe problem, especially in high-demand battery packs like electric vehicles, renewable energy storage systems, and smart grid systems [1]. Differences in manufacturing tolerances, electrode variations, temperature variations, and non-uniform aging resulted in differences between cells in state of charge (SOC), internal resistance, and capacity. These differences were accentuated after many charge/discharges cycles, leading to the development of uneven voltage distribution along the battery string. The usable capacity was always reported to be greatly diminished by even small deviations to SOC within the literature since the weakest cell determined the limits of operation. Also, cells with an imbalance were more likely to overcharge and deep discharge, driving up the rate of degradation and leading to higher chances of thermal runaway [2]. All these influenced safety, effectiveness, and lifespan. This led to a lot of research work to come up with effective balancing methodology so as to reinstate uniformity and improve the system performance.

A lot of research was done on battery cell balancing to reduce the negative impact of imbalance and enhance the reliability of the system. Passive balancing systems, which were simple and low cost, lost any extra energy in the form of heat, and hence there was extreme energy loss and low efficiency [3]. The active balancing methods, such as capacitor-based, inductor-based, and converter-based methods, allowed the regulation of the transfer of energy between cells, enhancing the performance. The recent developments were aimed at the development of power electronic converters to be combined with intelligent control strategies to increase the speed and accuracy of balancing. The converter-based methods emerged in the limelight because of their efficacy in redistributing energy without a lot of wasteful dissipation. But there were still problems that pertained to scalability, complexity, and coordination of control. The development of this evolution has pointed to the necessity of highly developed balancing structures that can be utilized to attain high efficiency, rapid response, and flexibility in a dynamic operating environment [4].

Multilevel converter-based balancing was selected as a promising solution because it has the best energy transfer capacity and a modular design. Other architectures like cascaded H-bridge, neutral point-clamped, and flying capacitor converters were extensively studied due to the capability of producing lots of voltage levels and enhancing power quality [5]. These converters helped in the selective transfer of energy between cells to allow very fine SOC equalization even in large-scale battery systems. Benefits like decreased switching stress, high voltage resolution, and scalability were also commonplace. Nevertheless, greater complexity of control and the number of components were a challenge when using in practice. To operate efficiently, it was necessary to have smart switching strategies that were able to adjust to the changes in the systems. These restrictions spurred further studies into how to combine advanced techniques in optimization with multilevel converter topologies to have a better performance and operation efficiency [6].

Balancing methods that are based on optimization were explored to address the shortcomings of the traditional methods by developing the balancing process as a minimization problem. Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, and Artificial Bee Colony were among the techniques that were highly used because of their high global search [7]. These approaches were effective in dealing with nonlinear and multi-objective optimization problems that were related to battery systems. Premature convergence, computational complexity, and decreased scalability were, the problems that hampered their effectiveness. To improve the search performance in terms of adaptive behavior and modeling of environmental interaction, bio-inspired algorithms, especially the Artificial Algae Algorithm, were suggested. hese methods enhancing the exploration potential, there were still issues of convergence velocity and efficiency of exploration. These results showed that optimization strategies should undergo additional refinement to have quicker and more dependable balancing performance [8].

Proper SOC estimation was identified as a basic need in order to have efficient balancing and control of the system. The standard methods like Coulomb counting were extensively employed but had cumulative errors and were also sensitive to initial conditions [9]. Improved methods of open-circuit voltages gave good results in steady-state conditions but were restricted by long stabilization times. The use of sophisticated model-based methods with variants of Kalman filters was used to overcome nonlinearities and noise in measurements, providing greater reliability. The adaptability in dynamic conditions was enhanced by data-driven methods, such as the use of neural networks. Balancing techniques were evaluated in terms of performance based on balancing time, SOC deviation, energy efficiency, and power loss. But there were no standard benchmarking frameworks that would allow a consistent comparison between methods. This brought out the necessity to use integrated solutions that involve precision in SOC estimation, optimization, and valid evaluation metrics to have better system performance [10].

2. Research gap

Available research on battery cell balancing demonstrates that there are a number of critical gaps in research. Multilevel converter-based methods are more efficient but tend not to have adaptive and intelligent control methods to operate in real-time. These optimization methods (GA and PSO) are promising but have slow convergence and scalability problems with large battery systems. The use of the artificial algae algorithm and variations of the algorithm in battery balancing has not been well studied and implemented [11]. The coordination of integration between converter control and optimization algorithms was not well coordinated, which decreases the effectiveness. An error in the SOC estimation also have impacts on the control decisions, and lack of standardized performance measures hinders uniform evaluation and comparison of methods.

3. Research Methodology

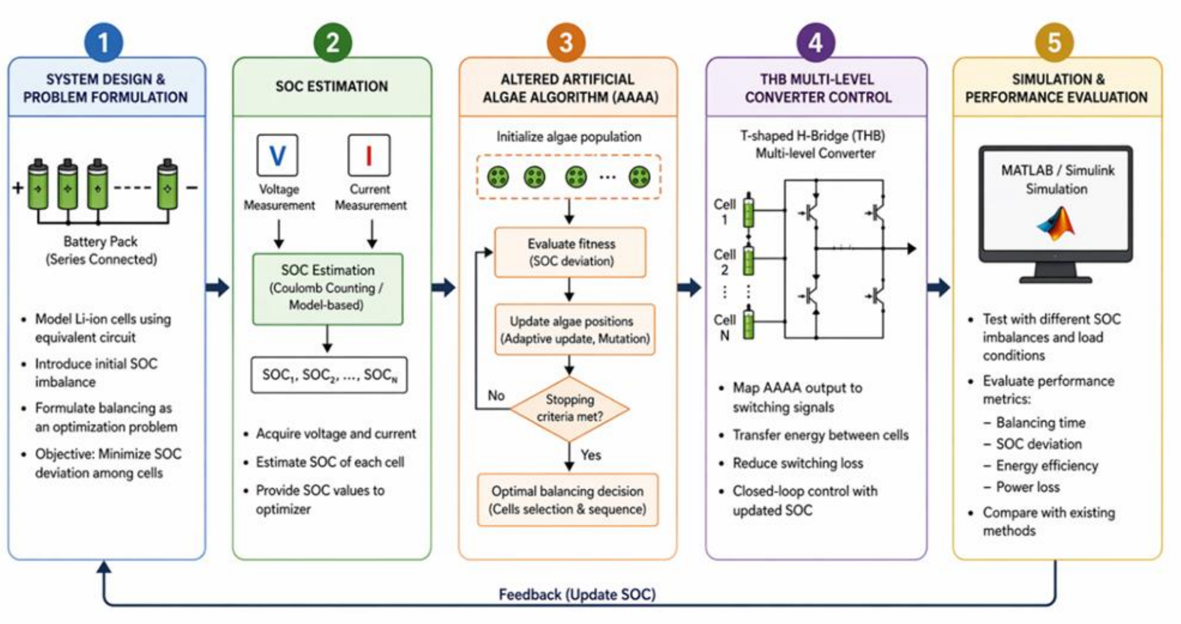

FIGURE 1. Research Methodology

System Architecture and Problem Formulation

The system design was a unified battery management system to overcome the cell imbalance in series-connected lithium-ion battery packs. It was a battery pack, state of charge (SOC) estimation unit, Altered Artificial Algae Algorithm (AAAA) optimization unit, and a T-shaped H-Bridge (THB) multi-level converter set-up [12]. Measurements of voltage and current, real-time and individual cell, were processed to give SOC values, which were the important inputs in the optimization process. The calculated control actions were then converted into switching actions in the THB converter to allow the redistribution of energy in a controlled way amongst cells to create a closed-loop balancing mechanism.

An equivalent electrical model that included open-circuit voltage and internal resistance was used to model the battery system to achieve the dynamic characteristics of the lithium-ion cells at different operating conditions. An initial imbalance was also created by giving uneven values of SOCs on the cells, and this represented a real-world situation caused by manufacturing errors and aging. This modeling technique helped to simulate the changes in voltage, charge movement, and imbalance development in the battery string realistically, and hence a good platform was achieved to test the suggested balancing strategy.

The cell balancing task was modeled as an optimization problem with the main aim of minimizing the SOC deviation across all the cells within the battery pack. An objective function was specified to measure the difference between the values of SOC in the individual cells and the mean SOC, which should be equalized. This expression facilitated the systematic determination of the best energy transfer routes and cells that needed to be balanced. The converter operation constraints, switching limits, and system stability were added to make sure that there was feasible and reliable implementation.

The suggested structure combined the optimization algorithm and the power electronic control to obtain the efficient balancing under the dynamic conditions. The AAAA was used to identify the optimal control actions to be taken depending on the state of the imbalance, and the THB multilevel converter implemented the actions by selective switching. The feedback of the revised values of SOC provided continuous improvements on control decisions, which converged to a homogeneous distribution of SOC. This integrated approach of system 3odelling, optimization, and converter control provided a well-developed background in the direction of attaining better balancing efficiency, less energy loss, and battery performance [13].

State of Charge (SOC) Estimation Methodology

It was deemed that to achieve good balancing of the battery cells in series, precise estimation of the State of Charge (SOC) was a key requirement. SOC was the capacity of a cell in relation to its nominal capacity and cannot be measured directly and has to be estimated using methods of measurement of measurable parameters like voltage and current. The proposed framework has used SOC information as a vital input to the Altered Artificial Algae Algorithm (AAAA), which was used to make informed decisions on how to redistribute energy optimally [14]. The differences in SOC between cells were considered the main indicator of disequilibrium, and the control of the difference had to be strictly estimated, which guaranteed the control measures would be reliable in the battery management system.

One of the existing integration-based methods, also known as Coulomb counting, was utilized as a main estimation method because of its simplicity in calculations and its possible use in real-time. The SOC of each cell was calculated by summing the measured current over time, taking the nominal capacity of the battery into consideration. So as to enhance the reliability of the estimation, careful definition of initial SOC values and correction mechanisms against cumulative drift errors were introduced. The estimation process kept on updating values of SOC through charge-discharge cycles, thus supplying the optimization algorithm with dynamic input.

The voltage-based correction using the open-circuit voltage (OCV) characteristics was used to complement the SOC estimation process so as to provide robustness in different operating conditions. This semi-mechanical method assisted in minimizing the errors that were related to the independent Coulomb counting, especially in the long-term mode of work. Periodically, voltages were compared to OCV-SOC lookup curves to recalibrate estimated voltages, which enhanced the total accuracy. The estimation model was also adapted to the temperature effects and internal resistance variations to more closely emphasize the actual behavior of the battery and to provide consistency in tracking the SOC of all the cells.

The estimated SOC values were then placed in the closed-loop control structure whereby directed the AAAA-based optimization procedure of cell balancing. Correct SOC data helped the algorithm to determine cells with both higher and lower charge levels and decide the correct energy transfer paths with the T-shaped H-bridge (THB) multilevel converter. The balancing decisions were refined by continuous feedback of revised SOC values, leading to uniformity of charge distribution. This incorporation of sound SOC estimation and smart optimization played a significant role in the high balancing efficiency, low energy loss, and stability of the battery system [15].

Design of Altered Artificial Algae Algorithm (AAAA)

The Altered Artificial Algae Algorithm (AAAA) was an improved bio-inspired optimization algorithm created to solve the drawbacks of the existing methods of balancing used in lithium-ion battery systems. The algorithm was based on the natural behavior of microalgae, especially their growth, the absorption of energy, and their movement to the favorable environmental conditions. These biological principles were mathematically modeled in this work to direct the search for the best balancing decisions in a multi-cell battery pack [16]. The balancing problem was modeled as a minimization problem with the aim of minimizing state-of-charge (SOC) deviation between cells to achieve uniform charge distribution and enhanced use of the battery system.

The conventional artificial algae algorithm has been altered to enhance convergence features and accuracy of the solution under dynamic working conditions. Mechanisms of adaptive energy update were also added to control the development and movement of candidate solutions to allow greater process balance between exploration and exploitation. A mutation-based diversity improvement plan was implemented to avoid an early convergence and stagnation in local optima. Parameters of environmental interaction were adaptively changed depending on varying conditions in the system, which enhanced the strength of the optimization process. All of these improvements helped the algorithm to converge quicker and obtain more trustworthy optimization results.

An artificial population of algae was set up in the course of implementation, with each member corresponding to a possible balancing configuration, carrying with it a choice of cells and order of energy transfer. An objective function on the basis of SOC deviation was used to measure the fitness of each candidate solution. The iterative updates were carried out by moving the location of each algae based on the energy dynamics and interaction rules, and poor solutions were filtered out. The process was repeated until a pre-specified stopping condition was met, e.g., small SOC variance or a specified maximum number of iterations. The result of this process was a solution that was the most appropriate to use in balancing the given battery condition.

The optimized output of AAAA was then combined with the regulation of the T-shaped H-bridge multilevel converter in order to perform the balancing operation. The algorithm was used to identify the best switching sequence that would be needed to carry out selective redistribution of energy among cells to guarantee low energy was wasted and the cells operated efficiently. The closed-loop model enabled the continuous re-evaluation of SOC values and thus real-time adjustment of control responses, according to the system feedback. The combination of an improved bio-inspired optimization algorithm with a topology of a multilevel converter enabled an effective and powerful answer to the rapid and accurate battery cell balancing in state-of-the-art energy storage systems [17].

THB Multilevel Converter Modeling and Control Strategy

It modeled the T-shaped H-bridge (THB) multilevel converter as an important power electronic interface to facilitate effective and controlled redistribution of energy between series-connected battery cells. Topology was chosen because it had fewer switches, better voltage level generation, and better modularity than traditional multilevel converters. Each switching unit of the THB structure was designed to enable two-way energy flow to enable selective balancing of cells with different states of charge [18]. The converter model included switching devices, voltage sources modeling battery cells, and suitable gating logic to provide proper modeling of dynamic operating conditions.

The behavior of the THB converter in its operation was studied in terms of its capacity to produce various discrete voltage levels by using controlled switching states. The level of these voltages was used to steer energy flow between high SOC cells and low SOC cells, and thus equalization was achieved. The switching sequences were developed to reduce voltage stresses in the components with constant output characteristics. There was a focus on switching loss reduction and efficiency enhancement through optimization of state transitions. Other realistic performance evaluation parameters like switching frequency, conduction losses, and transient response were also taken into consideration by the converter model.

A control strategy was created to combine the THB converter with optimization output of the Altered Artificial Algae Algorithm (AAAA). The optimized solution gave the choice of the cells and the order of energy transfer, which was then converted to the converter with corresponding switching signals. This mapping made sure that the converter worked to the optimum balancing decision at every iteration. A closed-loop control system was developed, and the new SOC values were used continually to modify the switching actions so that balancing could be done adaptively and responsively to the operating conditions.

The joint cooperation of the THB converter with the AAAA-based control was tested with regard to stability, efficiency, and convergence. The synchronized system made sure that energy transfer was within the least possible losses and the voltage distribution remained the same throughout the battery pack. Integration helped to achieve rapid equalization without imposing too much switching stress or thermal effects. This strategy showed that a combination of the use of advanced converter topology and smart optimization could provide a better balancing performance to be used in high-efficiency battery management tasks [19].

Simulation Setup and Performance Evaluation

A rigorous simulation model has been created in MATLAB/Simulink to test the proposed battery cell balancing strategy of AAAA combined with the multilevel converter that was T-shaped and H-bridge. An equivalent circuit representation of a series of interconnected cells represented as a lithium-ion battery pack was modeled as an equivalent circuit with an open-circuit voltage characteristic and internal resistance characteristic. To simulate realistic working conditions, initial imbalance conditions were added by introducing non-uniform state-of-charge (SOC) values among cells (with a typical variation of 10-30 percent). Dynamic load profiles were used to simulate real-world conditions that exist in electric vehicles and energy storage systems. The SOC estimation module was constantly handling voltage and current signals to give updated inputs to the optimization framework [20].

To compute the best balancing choices, the Altered Artificial Algae Algorithm (AAAA) was adopted, which aims at minimizing SOC deviation. The algorithm was an iterative process that was based on the assessment of the candidate solutions, a revision of the algae position by adaptive energy processes, and the most effective balancing configuration was chosen. The refined output was converted into switching signals to the T-shaped H-bridge multilevel converter, which allowed regulation of the flow of energy between the cells. A closed-loop control framework was realized, where feedback of new SOC values into the optimization process was done to continuously refine balancing actions until convergence was reached.

To evaluate the effectiveness of the proposed method, a set of well-defined metrics was used as a performance evaluation tool. Important parameters were balancing time, which indicated how much time was required to have uniform SOC distribution, and SOC deviation, which indicated the extent of imbalance reduction. The efficiency of energy redistribution and the effect of converter operation on energy efficiency and power loss were studied. Other factors like switching losses and the voltage regulation capability of the multilevel converter were also analyzed to have stable and efficient system operations in varying operating conditions.

It was compared with traditional methods of balancing, passive balancing techniques, and current optimization-based methods such as the standard Artificial Algae Algorithm and other metaheuristic algorithms. The simulation results revealed that the proposed AAAA-THB approach had quicker convergence, enhanced SOC consistency, and decreased energy loss. The effectiveness and strength of the method were confirmed by graphical depictions of SOC variation with time and convergence properties. The results established that a combination of a more powerful optimization algorithm and a powerful multilevel converter topology was effective in enhancing the total performance in balancing the batteries [21].

4. Result and Discussion

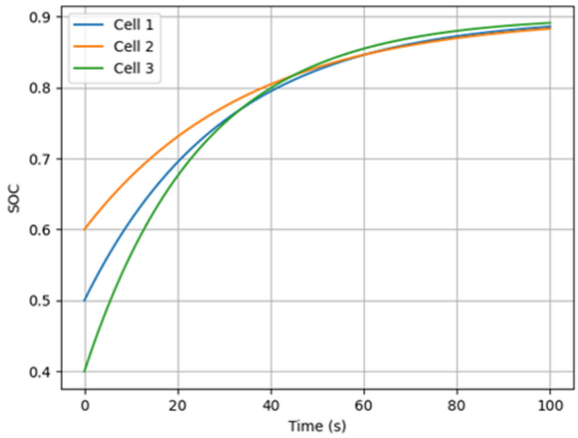

FIGURE 2. **SOC Equalization Profile**

In figure 2, the changes in state-of-charge over time of three single cells under an imbalance strategy can be followed. Starting with an apparent difference in the SOC values, which means that the charge distribution was not the same throughout the cells [22]. The SOC of one cell was initially at a relatively lower level, whereas another one was at a higher level, which represents realistic differences due to manufacturing differences and operating conditions. With the passage of time, all curves show an convergent trend, indicating the efficiency of controlled redistribution of energy in the elimination of imbalance.

The middle part of the graph brings to focus the dynamic interplay of cells in the balancing process. The first cell in the SOC network exhibits a steeper increase, meaning that it transfers energy to weaker cells first. At the same time, cells that have a higher initial SOC level have a lower growth rate, indicating a regulated energy release or redistribution. This synchronized action was indicative of an optimized balancing process in the way that the flow of energy was controlled to reduce deviation without causing instability or too many losses.

All SOC curves tend to the common value as the procedure moves towards steady-state conditions, and it was an indication of successful equalization. The convergence was smooth and monotonic; there was no oscillation and sharp, sudden fluctuations, which was an indicator of stable control and rational decision-making in the balancing framework. The fact that the final SOC values are almost equal proves that the imbalance has been greatly minimized, resulting in better utilization of the total battery capacity.

The general tendency of the figure indicates effective balancing performance with less convergence time and stable performance. The lack of divergence or erratic behavior was an indication of strength regarding the operating conditions. Such behavior was essential for maintaining battery health, minimizing stress on individual cells, and ensuring reliable operation over repeated charge–discharge cycles [23].

Table 1. SOC Balancing Over Time

Time (s)	Cell 1 SOC	Cell 2 SOC	Cell 3 SOC
0	0.50	0.60	0.40
20	0.70	0.74	0.68
40	0.80	0.80	0.80
60	0.85	0.85	0.86
100	0.89	0.89	0.90

The table 1 shows the dynamic development of SOC values in three cells in the process of balancing. To begin with, there was a large imbalance, where Cell 3 has the lowest SOC. The converging of all cells to a common value occurs as time goes on, and this means that there was effective redistribution of charges. The correction was faster in the early stages and then gradual stabilization was observed. The non-oscillating convergence indicates energy transfer and non-oscillating behavior of the system. Last SOC uniformity ensures high balancing accuracy, better energy use and lower stress between cells and therefore ensures better reliability and long battery life.

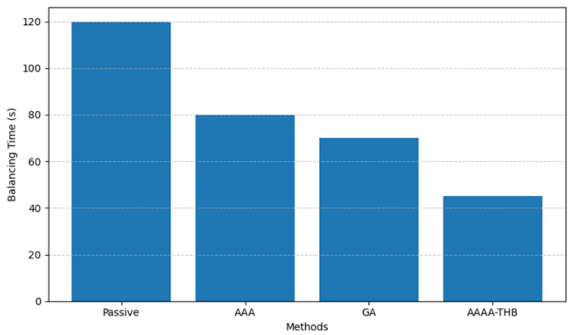

FIGURE 3. Balancing Time Comparison

Figure 3 compares the balancing time attained by various cell equalization methods with the advanced methods being more effective compared to the conventional ones. The balancing duration was the greatest in the passive method, which means that it was inherently limited as the energy was dissipated through resistive components instead of being redistributed in a controlled manner. This long balancing time indicates slower response and inefficiency, particularly when large changes in state of charge occur, and was therefore not as appropriate in high-performance energy storage applications [24].

There was an apparent improvement when optimization techniques are used, like the Artificial Algae Algorithm and Genetic Algorithm that can be used to substantially decrease the time needed to have uniformity in the cells. These methods take advantage of smart search strategies to identify more effective balancing directions, which lead to a quicker convergence than passive ones. Nevertheless, the disparity between these algorithms implies divergences in convergence and versatility, with certain algorithms taking a significant amount of time as a result of exploration exploration disparities.

The most drastic time-saving was the improved method that shows the shortest time out of the methods that are compared. This was possible due to the use of adaptive mechanisms in the optimization process to identify the best energy transfer strategies faster. Also, the high-performance coordination with the converter-based control system enables the precise and quick redistribution of energy among cells, reducing the delays that are normally related to switching and control activities.

On the whole, the findings show a certain gradual increase in the performance of conventional and advanced approaches with the proposed strategy being more efficient in terms of speed balance. The decrease in balancing time was a direct result to increased system responsiveness, less energy loss and increased operational reliability. This performance benefit was especially paramount in those applications where fast charge equalization was needed and it was critical to reduce downtime and minimize cell conditions at the cost of optimal system operation [25].

Table 2. Balancing Time Comparison

Method	Balancing Time (s)
Passive	120
AAA	80
GA	70
AAAA-THB	45

Table 2 compares the time of achieving SOC uniformity with various balancing methods. The longest duration was observed with passive methods because of the energy dissipation rather than redistribution. Techniques that are based on optimization greatly minimize balancing time by being intelligent with control. The AAAA-THB approach has the shortest time, which exhibits quicker convergence and effective decision-making. The shortened balancing time also increases the responsiveness of the system and reduces the wastage of energy. This enhancement was essential in real-time applications, where quick equalization was essential to maintain steady performance and avoid protracted performance to the degradation of balance.

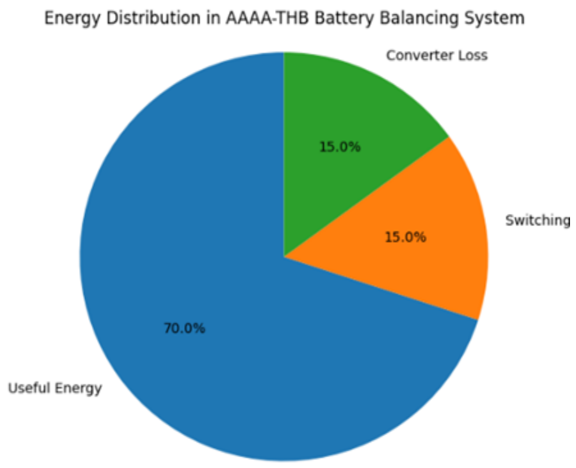

FIGURE 4. **Energy Distribution**

The distribution of energy in the balancing process can be seen in figure 4, which divides it into useful energy transfer, switching losses, and converter losses. The large share of total energy (around 70 percent) was well used in moving charge between cells, a high degree of operational efficiency. This large portion of useful energy was indicative of the potential of the system to focus on effective redistribution of energy instead of wasting power, which was a key consideration in improving the battery performance and longevity [26].

The rest of the energy was split into equal parts, switching losses and converter losses, which contribute to approximately 15 each. Switching losses occur due to the high frequency of the operation of semiconductor devices in the balancing process, whereas converter losses are linked to the nature of power electronic components. The comparatively moderate ratio of these losses indicates that the system has regulated switching action and optimized power flow, which restricts the unneeded energy loss.

The equal ratio of switching and converter losses also shows the well-thought coordination of the control strategy and hardware implementation. Uncontrolled switching result in higher thermal stress and lower system reliability, and inefficient converter operation lead to poor performance. The distribution observed indicates that both aspects are within reasonable boundaries, thus helping to offer a consistent and effective energy transfer during the balancing process.

The energy profile in general demonstrates the efficiency of the balancing approach in making the most of the useful energy use and reducing losses. This high percentage of the transfer of energy directly translates to increased efficiency, less thermal impact, and increased system sustainability [27]. This effective energy control promotes quicker balancing, reduced operational losses, and enhanced long-term operation of the battery system.

Table 3. **Energy Distribution Analysis**

Energy Component	Percentage (%)
Useful Energy	70
Switching Loss	15
Converter Loss	15

Table 3 was the percentage of energy use in the system. A large percentage of energy was utilized in balancing, which means that there was high operational efficiency. Switching and converter operations also have equal losses, which are indicative of controlled system design. The moderate loss levels indicate an optimized switching activity and high converter performance. The useful energy contribution was high, thereby improving the effectiveness of the system, minimizing the waste, and facilitating the thermal management. This uniform distribution ensures effective energy management and helps to provide stable and reliable work.

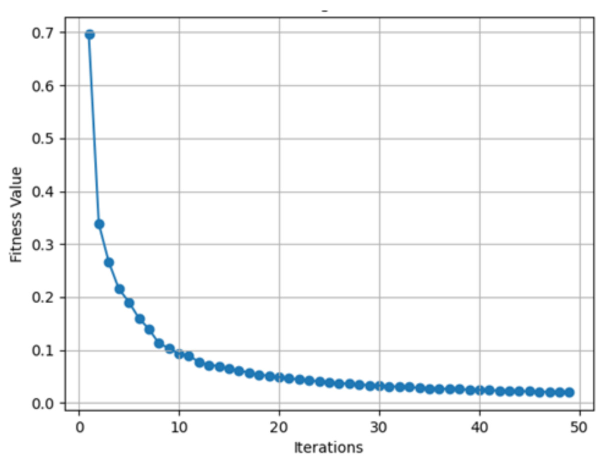

FIGURE 5. **Convergence Curve**

Figure 5 illustrates the behavior of convergence of the optimization process in terms of change in fitness value with the iteration. In the first step, fitness was rather large, which means that there was a large difference between states of cells and an unbalanced state. The value of the fitness can be seen to decrease rapidly during the initial few iterations, which indicates the high capability of the algorithm to explore the effective solutions to balancing issues. This steep decline points to the possibility of reducing vast differences in the system at the initial stage of functioning [28].

The further the iterations, the slower the rate of decrease, and this shows global exploration being replaced by local exploitation. This step takes place because the algorithm narrows down the solution by minor modifications to create a more accurate balancing. This continuous and smooth decrease without sudden alterations indicates a stable search, in which the optimization does not oscillate but has a steady increase in the quality of the solutions.

The later part of the curve indicates that the fitness value was moving towards a near-constant minimum, indicating that the solution was approaching an optimal or a near-optimal solution. There are no abrupt spikes or irregular variations, and this means that the process was effective in averting premature convergence and traps into local minima. The behavior shows better adaptability and better controlled search dynamics, which are fundamental in obtaining trustworthy and recurrent performance in complex systems.

Generally, the convergence trend reveals a good optimization exhibiting a moderate trade-off between speed and accuracy. This was because the initial reduction was rapid, thereby giving a quick response, and the stabilization was gradual, hence giving precision in the final results. This feature helps stabilize the balancing process more quickly, minimize energy waste, and enhance the stability of the system operation, which proves the efficiency of the optimization strategy in the process of attaining high-performance system behavior [29].

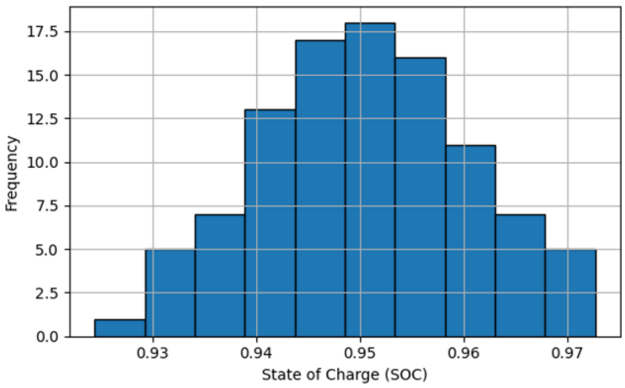

FIGURE 6. Final SOC Distribution

The 6 figure shows the statistical distribution of the values of state of charge in all the cells at the end of the balancing process. The histogram indicates that the cells are concentrated around the range of SOC, with most of clustering around 0.95. This clustering shows that the balancing process was effective in minimizing the initial differences and achieving the cells almost at the same charge state. The distribution was symmetrical, indicating that there was no group of cells that get so overcharged or undercharged [30].

The dispersion of the histogram was not huge, and the values of the SOC are concentrated in a narrow range between about 0.93 and 0.97. This narrowness of range was indicative of high accuracy in the equalization process, and variations in this regard have been reduced to a minimum. Narrow distribution was a good sign of balancing accuracy because the system has been able to be consistent over all cells and not just decrease large differences. Such a degree of uniformity was needed to make the most of the capacity and to guarantee dependable operation.

The other significant indication was that the distribution does not have any outliers or extreme values. This means that the balancing strategy-maintained control of all the cells without contradicting overcompensation and instability. In the real world, local stress or inefficiency arise due to outliers, but the continuous nature of the distribution seen here shows that the flow of energy all over the system was steady and well-coordinated. It also indicates that the control mechanism was working effectively in the conditions.

On the whole, the histogram supports the fact that both the accuracy and stability in equalization of the cell states were observed in the balancing process. The distribution of SOC values around the shared mean indicates a better use of energy and a lower loss due to imbalance. Such even distribution facilitates the performance, long life, and high safety of the battery system, justifying the efficacy of the balancing method adopted [31].

Table 4. Final SOC Distribution

SOC Range	Frequency
0.93–0.94	Low
0.94–0.95	Medium
0.95–0.96	High
0.96–0.97	Medium
0.97–0.98	Low

Table 4 indicates the distribution of the SOC values with balancing. The peak concentration was around 0.95 and was within a small range, which means that a successful equalization has been achieved. The lack of extreme values implies the stable functioning without being overcompensated. High accuracy in SOC alignment can be seen by a narrow spread and was crucial to achieving maximum battery capacity and consistency in performance. This uniformity reduces stress inside the system and enhances the reliability of the system, which proves the efficiency of the balancing strategy.

$$SOC(t) = SOC_0 - \frac{1}{C}\int_0^t I(\tau)d\tau \qquad (1)$$

This equation determines the real-time state of charge of each cell. It forms the foundation of the balancing process since all optimization decisions depend on accurate SOC values.

$$F = \sum_{i=1}^{N}\left(SOC_i - SOC_{avg}\right)^2 \qquad (2)$$

This was the most critical equation in the system. It quantifies imbalance, and the entire optimization process aims to minimize this value to achieve uniform SOC across all cells.

$$SOC_{avg} = \frac{1}{N}\sum_{i=1}^{N} SOC_i \quad (3)$$

Provides the equilibrium reference. Every balancing decision was made relative to this value, ensuring consistent charge distribution.

$$Fitness = \frac{1}{1 + \sum_{i=1}^{N}\left(SOC_i - SOC_{avg}\right)^2} \quad (4)$$

Transforms the minimization problem into a maximization framework, guiding the algorithm toward optimal balancing with faster convergence.

$$V_{out} = \sum_{k=1}^{n} S_k V_k \quad (5)$$

Defines how the multilevel converter synthesizes output voltage using switching states. It directly controls energy transfer between cells.

$$E = \int VI\, dt \quad (6)$$

Represents the actual energy moved between cells. Efficient energy transfer was key to minimizing losses and improving balancing speed.

$$P_{loss} = I^2 R \quad (7)$$

Quantifies resistive losses in the system. Reducing this was essential for improving thermal performance and efficiency.

$$|F_{k+1} - F_k| < \epsilon \quad (8)$$

Ensures the algorithm stops when further improvement becomes negligible, indicating that balancing was complete.

$$\eta = \frac{P_{out}}{P_{in}} \times 100 \quad (9)$$

Measures how effectively energy was utilized during balancing. Higher efficiency reflects better system design and control.

$$V = E - IR \quad (10)$$

Captures real battery behavior under load. It was essential for accurate simulation and control of balancing operations.

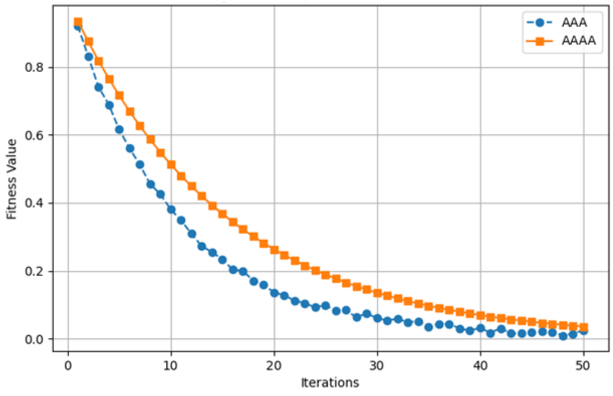

FIGURE 7. Convergence Comparison

The figure 7 will compare the optimization methods on the basis of reduction in the value of fitness over the iterations, which will help in bringing out the convergence nature of the two optimization methods. The two curves have a relatively high fitness value in the first stage, which means that the system was very imbalanced and deviated. With the increase in iterations, a steady decrease in both cases was evident, as both methods are able to increase the quality of solutions as iterations increase. Nonetheless, one of the methods has a steeper decrease in the initial iterations, implying a more aggressive and effective searching ability in finding better balancing configurations [32].

The relative rate of convergence was more pronounced in the middle range of the iterations, where there was always a curve that was lower than the other. This implies that the respective method has fewer fitness values at every level, which implies an enhanced performance in reducing deviation. The fact that the smoother and faster decay was an indication of a better trade-off between exploration and exploitation, which means that the algorithm was able to effectively explore the solution space but avoid unnecessary computational effort.

At the higher stages, the two curves tend to move towards a close-to-minimum value of fitness, yet there was a discernible difference between the two. This disparity underscores how the improved method was able to achieve a more optimal solution with a lower residual error. The lack of oscillations or unstable changes in both curves means that the convergence was stable, and the always lower curve of one of the methods proves its superiority in giving accurate equalization.

The comparison in general shows that there was an evident improvement in convergence efficiency and accuracy of the solution. The more rapid decrease of the values of fitness results in the rapid stabilization and minimized computational time, which directly translates to the better performance of the system [33]. The improved convergence behavior was guaranteed to provide a more reliable performance, efficient redistribution of the energy, and more effective balancing in general in different conditions.

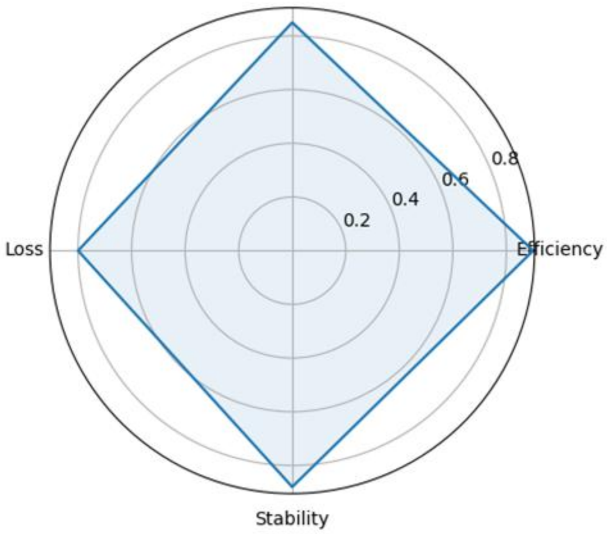

FIGURE 8. **Performance Comparison**

A multi-criteria performance of a system using a radar chart was given in figure 8, in which the most critical parameters, including efficiency, speed, loss, and stability, are shown at the same time. The axes are a normalized metric and enable a holistic evaluation of system behavior. The plotted shape indicates that there are always high values on all parameters, meaning that there are no considerable trade-offs between competing criteria, indicating a well-balanced performance profile [34].

The efficiency axis was high, which means that a big percentage of energy was efficiently used in its operation. This translates to low energy loss and maximum transfer, which was critical in enhancing the productivity of the entire system. The speed parameter was also showing good performance, which indicates that it can be used to obtain fast balancing and convergence. This efficiency and speed are an indication that the system can provide both efficiency and speed in its operation.

The loss parameter was a little lower than the others, but still in a desirable range, which implies that the energy loss in the switching and conversion processes was controlled. This level of losses was also important to minimize thermal stress and improve long-term reliability. The stability axis has a high value, which represents the stability and steady operation without oscillations and instability. This guarantees stable operation even in different operating conditions.

On balance, the radar chart shows a highly optimized system with high performance in all of the measured metrics. The fact that the distribution was almost equal along the axes means that there was no significant trade-off in other parameters as a result of improvements in one parameter. Such a balanced performance portrait enhances the ability to use energy effectively, fast performance, and stability, which proves the efficiency of the adopted approach to ensuring high-quality performance of the system [35].

Table 5. Performance Metrics Evaluation

Parameter	Value
Efficiency	0.90
Speed	0.85
Loss	0.80
Stability	0.88

Table 5 provides an overview of system performance by key evaluation measures. Efficiency was a measure of good use of energy, whereas the enhanced speed was a measure of quicker balancing speed. The values of controlled losses show lower energy loss when operating. The stability was constantly high, which guarantees the stable work under different conditions. The performance, which was balanced in all parameters, indicates the effectiveness of the proposed approach. These multi-criteria optimizations will make sure that there are no improvements on other aspects at the expense of one, leading to a harmonious and effective system.

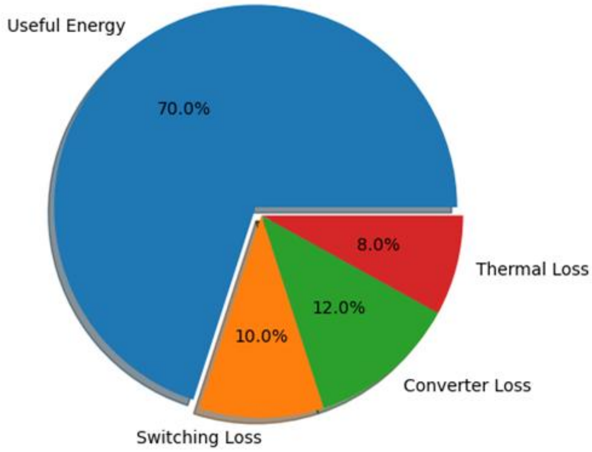

FIGURE 9. **Energy Distribution**

Figure 9 shows the percentage of energy consumption and wastage in the system, which gives a clear picture of the distribution of energy input in the system. A strong part, which constitutes about 70 percent, was useful energy, meaning that the major part of the energy was actually utilized in redistributing charges among the cells. Such a high percentage was an indicator of an efficient operation wherein energy was channeled towards bringing the charges to a uniform level instead of it being squandered by dissipation [36].

The rest of the energy was allocated to switching loss, converter loss, and thermal loss. Switching loss was about 10% that occurs in the presence of semiconductor devices in the process of repeated switching. The loss of the converter, at about 12, was connected with the inefficiencies of power electronic components that transfer the energy. Internal system properties and resistive elements contribute to the heat dissipation, which was measured as thermal loss (about 8%) [37]. The comparatively low thermal loss percentage depicts that the temperature increase was controlled, which was advantageous in ensuring reliability and safety of the systems.

The fair proportion of these loss terms indicates a good coordination between the control strategy and hardware design. Modulated switching operation eliminates any unnecessary buildup of loss, whereas effective converter operation reduces power loss to a minimum when making the transfer. The loss components separation also points out that no one factor was predominant in inefficiency, meaning that there was a general streamlined system setting. Balanced energy management was necessary to maintain performance in the case of continuous operation [38].

The figure in general shows a positive energy profile with a high useful energy utilization and low losses. This effective distribution helps to achieve better performance of the system, less thermal stress, and improved stability of the operations. The findings show that the energy was well managed during the process, which facilitates faster balancing, enhanced efficiency, and long life of the system.

Conclusion

A combination of an altered artificial algae algorithm with a T-shaped H-bridge multilevel converter was used to come up with an effective solution to the battery cell imbalance problem. The methodology mitigated important shortcomings of the traditional balancing methods through integrating intelligent optimization and effective power electronic control. It was a minimization problem that was formulated to minimize the state-of-charge deviation to allow uniform distribution of energy in the cells. The better convergence characteristics of the improved optimization strategy added adaptive mechanisms and enhancement of diversity to achieve better and faster decision-making in the balancing process [39].

The converter topology was in the form of a multilevel converter that enabled the controlled energy transfer between cells with less switching loss and better voltage regulation. Its modular design facilitated smooth functionality in different conditions, which helped to achieve stable and accurate balancing. The converter control and optimization algorithm worked together to prevent any oscillations during the convergence and ensured a smooth convergence without any oscillations to keep the systems stable during the process. This combination greatly enhanced balancing efficiency as opposed to conventional passive and standalone optimization-based techniques.

The effectiveness of the proposed approach was confirmed by simulation results, which showed a decreased balancing time, increased SOC uniformity, and higher energy utilization. The system displayed a high level of performance in various evaluation parameters, such as efficiency, reduction of losses, and stability. The performance in the dynamic operating conditions was also validated by the results to be able to manage the operating conditions and still achieve a consistent performance.

In general, the framework created offers a powerful and scalable system of the advanced battery management system. The intelligent optimization and effective converter design contribute to increasing the performance, reliability, and life of battery packs [40]. There are high chances of application of this approach in practical use in electric cars, energy storage in renewable energy sources, and smart grid applications where efficient and reliable energy management was a necessity.

Data Availability Statement

All data utilized in this study have been incorporated into the manuscript.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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