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An Improved Thermal Management of Lithium-Based Batteries Employing Genetic Algorithm Optimization

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Abstract.. Lithium-based battery systems (LBS) are used in various applications, from the smallest electronic devices to power generation plants. LBS energy storage technology, which can offer high power and high energy density simultaneously, can respond to continuous energy needs and meet sudden power demands. The lifetime of LBSs, which are seen as a high-cost storage technology, depends on many parameters such as usage habits, temperature and charge rate. Since LBSs store energy electrochemically, they are seriously affected by temperature. High-temperature environments increase the thermal stress on the LBS and cause its chemical structure to deteriorate much faster. In addition, the fast charging feature of LBSs, which is presented as an advantage, increases the internal temperature of the cell and negatively affects the battery life. The proposed energy management approach ensures that the ambient temperature affects the charging speed of the battery and that the charging speed is adaptively updated continuously. So, the two parameters that harm battery health absorb each other, and the battery has a longer life. A new differential approach has been created for the proposed energy management system. The total amount of energy that can be withdrawn from the LBS is increased by 14.18% compared to the LBS controlled with the standard energy management system using the genetic algorithm optimized parameters. In this way, the LBS replacement period is extended, providing both cost benefits and environmentally friendly management by LBSs turning into chemical waste later.

Key words: Lithium-Ion Battery; Temperature; Energy Management System; Renewable Energy; Genetic Algorithm

1. INTRODUCTION

In recent years, the increasing need for energy by developing technology and increasing environmental concerns have led people to renewable energy sources [1]. According to data from the National Energy Agency, fossil fuel consumption is projected to increase by 0.7 times by 2050 unless energy consumption habits are changed. This could lead to a 1.3-fold increase in carbon emission rate and a 6 degree rise in global temperature [2]. Renewable energy systems (RES) are seen as the most excellent alternative to fossil fuel exhaustibility and environmental impacts. Due to their sustainable and environmentally friendly energy, RESs are expected to play a significant role in the future energy world. Renewable energy sources (RES) do not have the emissions caused by fossil fuels and are seen as the energy source of the future thanks to their sustainable nature [3], [4], [5]. However, although sustainable, RESs depend unpredictably on nature and are not a continuous energy source. For example, solar energy systems cannot produce energy when the sun is not shining, or wind energy systems require wind speed to be within certain limits to generate energy [6]. RESs are combined with other energy sources or integrated into energy storage systems to overcome these problems. In this way, it is possible to provide a stable and fluctuation-free power flow to the load [7].

Energy Storage Systems (ESS) can store and use excess energy when needed. Many energy storage techniques exist, such as physical, electromagnetic, chemical and electromechanical. The battery system is the most widely used storage unit, and it is based on an electrochemical method [8], [9]. Numerous battery types, such as lithium-ion, sodium-sulfur, nickel-cadmium, vanadium-redox and polysulfide bromine and lead acid batteries, are used in various fields [10], [11], [12]. Lithium-based batteries (LBS) offer high power and energy density simultaneously and have the highest utilization rate. Their high energy density allows them to meet long-term low power demands, while their high power density allows them to meet instantaneous high power demands. In addition to all these advantages, LBSs have the disadvantage of high cost. Therefore, it is necessary to extend the battery's life as much as possible and delay its replacement [13]. Batteries, which are indispensable for electric vehicles, have several concerns. LBS can cause dangerous and unwanted chemical reactions when charged at

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extreme temperatures. This can shorten battery life and, in worse scenarios, lead to safety risks such as fire.

LBSs need to operate under the control of a Battery Management System (BMS) to ensure high performance and long-lasting life. LBS performance of LBSs decreases over times the calendar ages[14], [15]. This occurs for two reasons: The first is the loss of lithium ions due to the formation of solid electrolytic contact. The second is electrode loss. This situation increases internal resistance, reducing capacity and efficiency and shortening battery life. As both of these occur as a result of irreversible chemical reactions, batteries need to be operated in a controlled manner. High temperatures can affect lithium-ion batteries' performance and lifespan, significantly accelerating their deterioration. The battery loses capacity as the solid electrolytic contact grows. This is because the rapid growth of solid electrolytic contact on the surface of the electron particles causes the battery to lose its capacity. Furthermore, the temperature of the environment significantly affects the rate of capacity loss. Battery cell temperature and high environmental conditions can cause solid electrolytic contacts to overgrow. Their development also reduces the battery capacity.

Parameters measured directly by sensors, such as current, voltage and temperature, can be used as regulators or drivers in BMS [16], [17]. For high performance, battery parameters such as SoC, C-Rate, and Depth of Discharge are required, which are indirectly estimated and predicted [18], [19]. Furthermore, one of the most critical parameters affecting ESS reliability and performance is temperature [20], [21], [22]. It is possible to determine whether the system is operating within the safe temperature range and to detect potential problems in advance by monitoring the temperature data of the ESS obtained by sensors. In addition, abnormal performance degradation that may be due to the effect of temperature can be detected, temperature-appropriate management can be provided, system failures can be prevented, efficiency can be maintained at consistently high levels, and energy security can be ensured through downtime reduction. The temperature parameter can be used as a safety and performance indicator of the energy management system (EMS), as well as part of an algorithm which controls the operation of the EMS with the temperature parameter as input [23]. In the development of strategies to increase the lifetime of components and to realize the longevity perspective, the use of the parameter of the internal cell temperatures of the batteries and the external temperatures as an input to the EMS plays an essential role[24], [25], [26].

Thermal runaway should be mentioned first to deal with temperature problems in general. A temperature curve and peak heat dissipation typically mark battery overheating. It consists of three stages: the abnormal generation of heat, the initiation of a fire and the explosion, which correspond to specific temperature thresholds[27]. Thermal runaway events can be classified into two paths: internal and external. The internal pathway refers to thermal failures caused by chemical reactions inside the cell, while the external pathway refers to smoke and fire observed outside the cell [28]. Both internal and external, thermal runaway is hazardous for safety. When the literature is examined, it is seen that there are many studies on battery cooling systems and battery thermal management systems (BTMS) to protect against thermal runaway [29], [30], [31], [32], [33]. Studies have been done on the battery with an external cooling system [34], [35] or to cool the battery with chemical structure and material science [36]. First of all, this situation causes extra cost. Secondly, cooling systems have serious disadvantages, such as the area they cover and the energy they consume from the battery. The proposed study uses the temperature parameter as the primary management input; in cases where the temperature increases, the aim is to eliminate other reasons that cause the temperature to improve and reduce the effect of the battery temperature in this way.

The parameter that determines charge and discharge rates, also known as C-rate, is another critical element that can be used in ESSs [37]. The C-rate is crucial for evaluating the performance of cells and batteries in energy storage systems. C-Rate expresses a cell or battery's charge/discharge rate relative to its rated capacity. This parameter is crucial for BMSs to monitor, control and optimize battery performance. A battery's C-rate indicates how quickly it can store or release energy. This information determines how your battery will respond to sudden energy needs, ensuring optimal power [38], [39]. The current at which the battery is being charged can also be controlled using this parameter. By using the C-rate parameter as a control argument, the EMS increases the life and performance of the battery by ensuring that charging and discharging take place at the optimum value. In this way, the cost of the battery is reduced, and the system's safety is improved [40].

In temperature scenarios, battery capacity loss significantly increased [41]. Batteries used in high-temperature environments without taking precautions will not perform at full capacity and will age rapidly. For example, the battery is stressed, and chemical degradation accelerates when used at high temperatures. As a result, the temperature parameter should not be ignored in the design of an advanced BMS. The responses of the battery to C-rate values at different temperatures are experimentally demonstrated in [42]. The effect of the heat produced by the battery on the charging/discharging characteristics was also studied. [43], another study using temperature as a direct control parameter alongside the primary control mechanism has a tangible impact on the charging-discharging rate. The reference current value is divided into three different zones according to temperature to reduce the stress caused by temperature. As a result of the study, the system's efficiency was measured to be 97.6 per cent.

In the proposed study, a BTMS was developed that provides a C-rate parameter that will be adaptively updated with the temperature value to increase the lifetime of the battery operating in high-temperature conditions. Due to the thermal stress caused by increasing battery cell temperature, the battery charging rate significantly impacts battery health.

High-speed charging technologies offer time advantages. However, they irreversibly damage the battery chemistry. The proposed study aims to adaptively reduce one of the two factors that adversely affect battery health when one of them increases, using a differential approach. By reducing the thermal stress caused by the charge rate, the aim is to offset the thermal stress caused by the temperature rise. A weighting parameter ζ was added to the differential approach developed to balance between the two factors. The optimization of ζ parameter is optimized by using a genetic algorithm.

The contribution of this study to the literature is the design of a BMS in which the temperature is taken as a basis, and the charging current is adaptively updated depending on the temperature to increase the lifetime of the batteries.

The main contributions of this paper are as follows:

1. Design and genetic algorithm optimization of a new adaptive energy management system for lithium-based batteries, where the ambient temperature is taken into account, and the charging rate is adaptively updated accordingly to extend the life of the batteries.
2. Ensuring the performance and safe operation of batteries under high temperatures and ensuring battery and user safety by reducing temperature-induced chemical stress without any cooling system
3. Reducing environmental waste generation and battery replacement costs by extending battery life

This paper is organized as follows: Firstly, the thermal model of lithium-based batteries is explained. Then, the flowchart of the proposed study is presented. Then, the impact of the temperature and C-Rate on the LBS are investigated. Finally, the BTMS simulation studies are analyzed and demonstrated to be superior.

2. MATERIAL and METHODS

The following equations for the Li-ion battery type represent the effect of temperature on the model parameters. The equations for the charging model and the discharging model will be analyzed separately. First, the discharge model's equations are given in equations 1 and 2 below.

$$\mathrm{f}_1(\mathrm{it}, \mathrm{i}*, \mathrm{i}, \mathrm{T}, T_a) = E_0(T) - K(T) \cdot \frac{Q(T_a)}{Q(T_a) - it} \cdot (i * + it) + A \cdot exp(-B \cdot it) - C \cdot it \tag{1}$$

$$V_{batt}(T) = f_1(\mathrm{it}, \mathrm{i}*, \mathrm{i}, \mathrm{T}, T_a) - R(T) \cdot i \tag{2}$$

For the charging model, the following equations are given.

$$\mathrm{f}_1(\mathrm{it}, \mathrm{i}*, \mathrm{i}, \mathrm{T}, T_a) = E_0(T) - K(T) \cdot \frac{Q(T_a)}{it + 0.1 \cdot Q(T_a)} \cdot i * - K(T) \cdot \frac{Q(T_a)}{Q(T_a) - it} it + A \cdot exp(-B \cdot it) - C \cdot it \tag{3}$$

$$V_{batt}(T) = f_1(\mathrm{it}, \mathrm{i}*, \mathrm{i}, \mathrm{T}, T_a) - R(T) \cdot i \tag{4}$$

Next, the effect of the battery temperature is considered by calculating the Nernst/Arehenius thermoelectric potential, the polarising constant and the internal resistance [44].

$$E_0(T) = E_0 \mid T_{ref} + \frac{\partial E}{\partial T}(T - T_{ref}) \tag{5}$$

$$K(T) = K \mid T_{ref} \cdot exp\left(\alpha\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)\right) \tag{6}$$

$$Q(T_a) = Q \mid T_a + \frac{\Delta \mathrm{Q}}{\Delta \mathrm{T}} \cdot (T_a - T_{ref}) \tag{7}$$

$$R(T) = R \mid T_{ref} \cdot exp\left(\beta\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)\right) \tag{8}$$

Where C is the nominal discharge curve slope, T is the cell temperature, Ta is ambient temperature, E/T is the temperature coefficient of reversible voltage, α and β are the Arrhenius rate constants for the polarization resistance and internal resistance respectively, ΔQ/ΔT is the maximum temperature coefficient of the capacitance, Tref is the ambient temperature [45]. The relationship between temperature internal resistance and power loss is also given in equation 9.

$$\mathrm{T}(t) = L^{-1}\left(\frac{P_{loss} R_{th} T_a}{1 + s \cdot t_c}\right) \tag{9}$$

Where Rth is the temperature-dependent resistance, tc is the temperature-dependent time constant, and Ploss is the power dissipation due to heat generation. The number of battery cycles is expressed by N in the expression. The temperature and the C-Rate are closely related. The proposed study is based on the relationship between these two parameters and how they affect the battery's cycle life.

$$N(n) = H\left(\frac{DOD(n)}{100}\right)^{-\xi} \cdot exp\left(-\psi\left(\frac{1}{T_{ref}} - \frac{1}{T_a(n)}\right)\right) \cdot \left(I_{dis\_ave}(n)\right)^{-\gamma_1} \cdot \left(I_{ch\_ave}(n)\right)^{-\gamma_2} \tag{10}$$

3. PROPOSED TEMPERATURE-BASED CONTROL FUNCTION

The dynamics of the battery performance concerning the ambient temperature are crucial for optimizing the battery's capacity and longevity. Equation 7 shows the direct relationship between battery capacity and ambient temperature, with capacity degradation when the temperature deviates from an established benchmark. This reference point was set at 25°C, the nominal ambient temperature for measurements. This ambient temperature is crucial as it is considered ideal for the battery to operate, providing optimum conditions for performance and durability. Taking the thermal effects a step further, equation 10 shows how ambient temperature affects battery capacity and significantly impacts the number of charge cycles and overall battery life. This relationship highlights the need to manage thermal conditions to maintain battery integrity. Specifically, high temperatures can accelerate degradation processes within the battery, reducing its life and reliability.

Therefore, understanding and controlling temperature effects is critical to improving battery performance throughout their operational lifetime. The proposed BTMS uses a novel approach to dynamically adjust the charge current to overcome the problems associated with high ambient temperature. As shown in Eqs. 11, 12, and 13, BTMS employs a differential approach for changing the charge current based on the deviation from the reference temperature and minimizes the thermal stress on the battery by reducing the charging current in response to increased temperature. This adaptive charging strategy is critical in high-temperature environments, where the risk of exacerbating thermal degradation is significant.

$$C_{rate} = \frac{I_{ch}}{I_{nominal}} \tag{11}$$

$$\Delta T = \frac{T_a - T_{ref}}{T_a} \tag{12}$$

$$C_{rate}(\mathrm{n}) = C_{rate}(\mathrm{n}-1) - \zeta * \Delta T \tag{13}$$

Ultimately, this adaptive approach reduces the adverse effects of high temperatures on battery chemistry and increases battery life. BTMS effectively slows down the degradation processes and extends the battery's life by applying a lower charge current as temperatures rise. This strategy allows the batteries to operate within more secure thermal parameters, preserving their capacity and prolonging their life under varying environmental conditions. Active thermal management through intelligent charge adjustment represents a significant step forward in battery technology. It offers a practical solution to one of the most pressing challenges facing battery management systems. Figure 1 shows the flow diagram of the proposed BTMS.

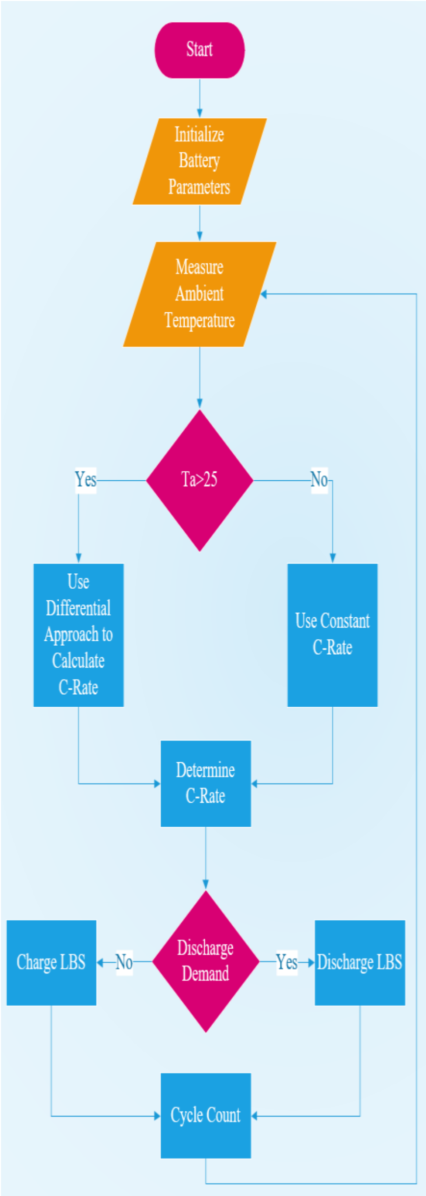

Fig. 1 Flowchart of the proposed battery management approach

4. SIMULATION STUDY

Table 1 gives information about the Powerbrick+ LiFEPO4 battery used in the simulation studies. A Simulink diagram was created using Matlab for simulation studies to minimize the effect of temperature on the battery and optimize the temperature and charge rate process.

The simulation diagram consists of the battery and control blocks, the block containing the proposed algorithm, and the blocks that perform the power calculations, as shown in Fig. 2. In this way, the system dynamics and control mechanisms are modelled in detail. The proposed algorithm controls the temperature in each cycle, determines the charging rate of the system according to the temperature value, and generates control signals.

TABLE 1 Battery Fabrication Parameters

Parameter	Value
Nominal Voltage	12.8 V
BOL Capacity	40 Ah
Cut-Off Voltage	10.5
Nominal Current	20 A (0.5C)
EOL Capacity	40*0.8 Ah
Nominal Charge Current	20 A (0.5C)
BOL Internal Resistance	0.015 Ohm
EOL Internal Resistance	0.01512 Ohm
Stored Energy	512 Wh
Mass	5.25 kg
Max Discharge	2C

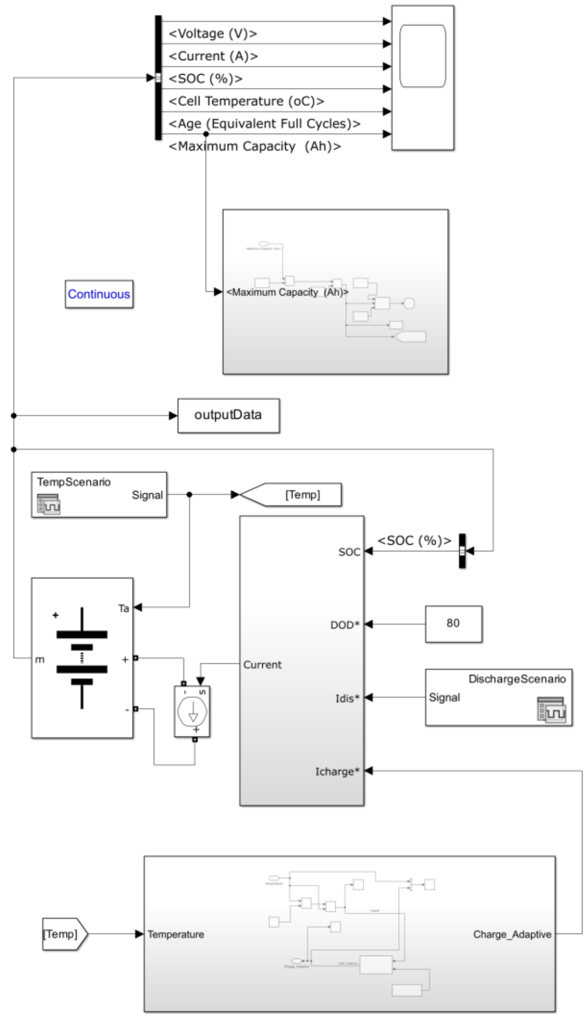

Fig .2 Simulink model of the proposed system

The battery block contains electrochemical and thermal models of the battery. Battery parameters such as voltage, current and temperature are continuously monitored and controlled. These components are critical to simulate the battery's instantaneous operating conditions accurately. The control block is used to optimize the performance of the battery system, extend its life and ensure its thermal safety. These blocks monitor the operating conditions of the battery and generate control signals. The proposed algorithm focuses on the temperature control of the battery and updates the charge rate by controlling the temperature value of the battery in each cycle. The algorithm consists of three steps: temperature measurement, decision-making, and control signal generation. In the temperature measurement step, the sensors take the current temperature values. The decision step determines the appropriate charge rate according to these temperature values. In the control signal generation step, the control signals required to adjust the charge rate are generated and applied to the system.

Figure 3 shows the amount of energy the system can produce during its lifetime operating under a constant C-Rate under varying temperature conditions. While 625 kWh of energy can be obtained from the battery at 25 degrees nominal temperature, this value decreases to 503.92 kWh at 35 degrees. In regions with high summer temperature averages, such as the Middle East and South America, this value drops to 411.75 kWh.

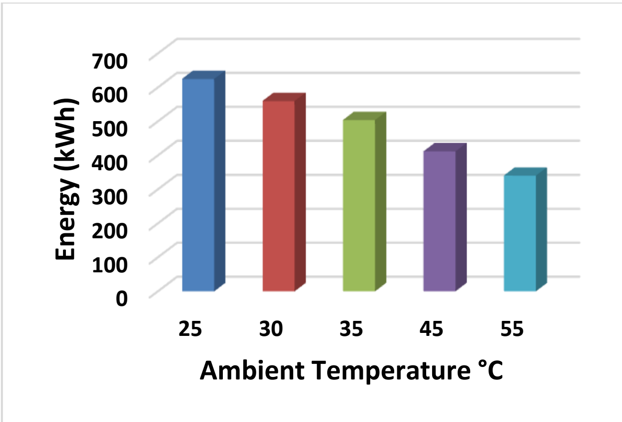

Fig. 3 Total energy provided by whole battery life under varying cell temperature

In desert regions, which we call extreme temperatures, the battery can produce 340.47 k Wh of energy under a constant C-Rate value. As can be seen, as the temperature increases, the battery's life decreases significantly due to the thermal stress on the battery.

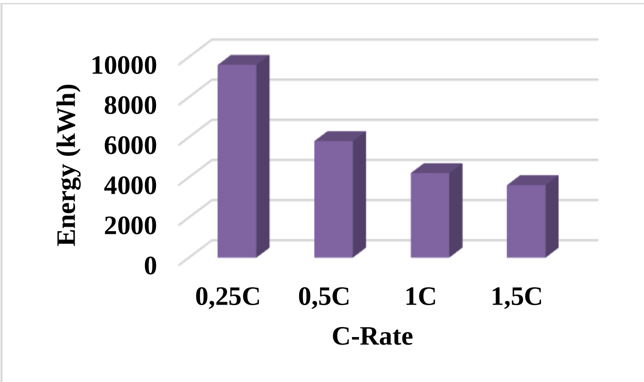

Fig. 4 Total energy provided by whole battery life under varying C-Rate values

When the battery is analyzed in terms of C-Rate under constant temperature, which can seen in Fig. 4, it is seen that the battery life decreases in parallel as the charging rate increases. When we discharge with 1.5C, 3612.4 kWh of energy can be withdrawn, and when we reduce the battery charging rate by 33% and charge with 1C, 4205.25 kWh of energy is provided. Similarly, when we reduce it to the minimum and charge it with 0.25C, the energy that can be drawn is 9608.09 kWh, but it should be noted that the lower the C-Rate value, the more the expected time for charging will increase. Therefore, it is essential to establish a balance and optimization between time and battery life.

4.1. Weighting Parameter Optimization By Genetic Algorithm

The genetic algorithm (GA) is an evolutionary algorithm inspired by the processes of biological evolution. It operates on a population of solution candidates and mimics the mechanisms of selection, crossover and mutation, which are the basic principles of natural selection. In each iteration, the most suitable individuals are selected, crossed to produce new individuals, and diversified by random mutations. This process continues until a set stopping criterion is met and usually produces results close to the best solution. Genetic algorithms are suitable for complex and multidimensional optimization problems and have a high probability of reaching the global optimum.

In this section, the weighting parameter ζ, which controls the rate at which the C-Rate decreases with each charging cycle, is optimized. The ζ parameter dynamically adjusts the initial C-Rate value at each cycle and aims to maximize the energy output while extending the battery life.

4.1.1. Cost Function

The cost function evaluates the effect of dynamic C-Rate changes controlled by the parameter ζ on the battery performance. It optimizes the value ζ over the battery life and total energy amount. The proposed cost function is given as equation 14:

$$J(\zeta) = -\int_0^{L(\zeta)} E(t,\zeta)dt \tag{14}$$

Here, E(t,ζ) is the amount of energy withdrawn during the battery life depending on the C-Rate determined by time t and weight parameter ζ. L(ζ) is the battery lifetime calculated depending on the value of ζ. J(ζ) calculates the total energy output depending on ζ and tries to maximize this value. Equation 15 finds the expression ζ* to minimize the cost function.

$$\zeta^* = argmin_{\zeta}.J(\zeta) \tag{15}$$

4.1.2. Optimization Process

The optimization process uses a genetic algorithm to determine the optimal value of the parameter ζ according to the flowchart in fig.5:

1. Starting Population: Starts with various values of ζ.
2. Simulation: For each ζ the battery model is simulated, and E(t,ζ) and L(ζ) are calculated.
3. Cost Evaluation: J(ζ) is calculated for each ζ.
4. Genetic Algorithm: Selection, crossover and mutation are carried out until the value of ζ that gives the lowest J(ζ) is found. This model can provide more efficient energy utilization and battery life in battery management systems. The optimal value of the ζ parameter optimally balances the energy efficiency and the battery's lifetime.

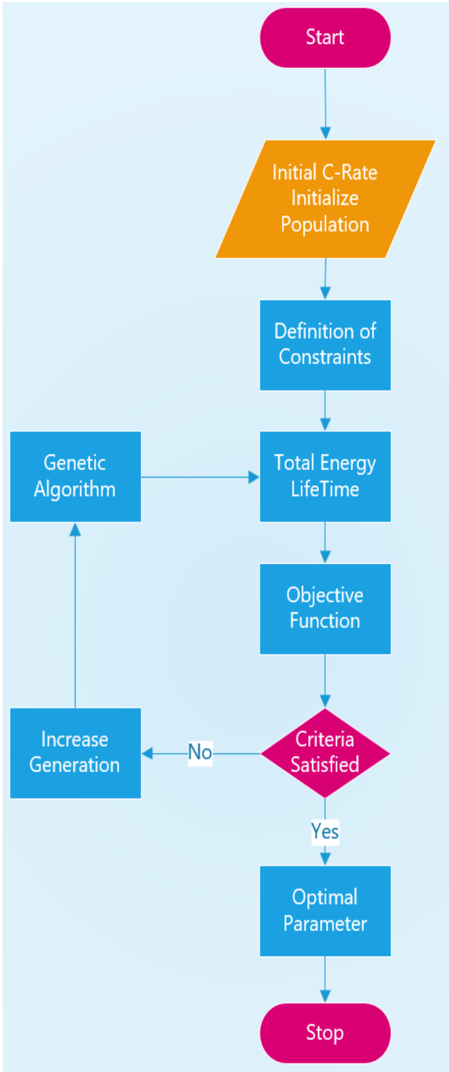

Fig. 5 Genetic Algorithm Optimization Flowchart

The optimization studies have shown that the best result in terms of time and energy is obtained from ζ=13.45. Figure 6 shows the cost function minimization by the genetic algorithm. The optimum ζ parameter found by the genetic algorithm considers the total energy that can be obtained and aims to ensure that the extended charging times are acceptable.

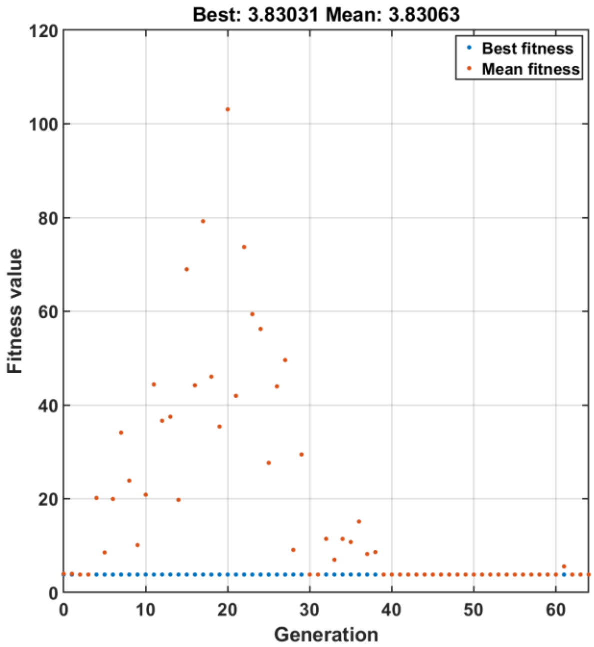

Fig. 6 Cost function minimization by the genetic algorithm

4.2. Case Study I: Constant Load Profile

Firstly, a constant load causing a constant 1C discharge at the output was used. Figure 7 shows the temperature profile used. The battery was tested at different temperatures during its lifetime. A separate C-Rate was determined for each temperature cycle using the proposed approach. Using four different ζ parameters, the variation of the charging current values obtained is given in Fig. 8, and the corresponding C-Rate values are presented in Fig. 9.

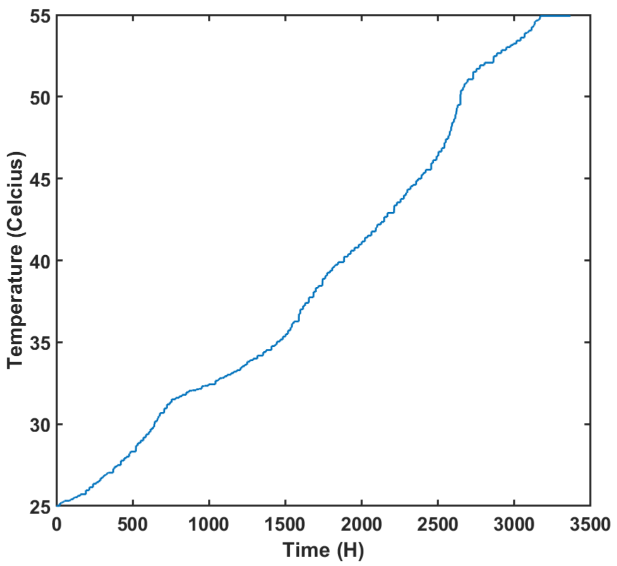

Fig. 7 Temperature Profile of the Simulation Studies

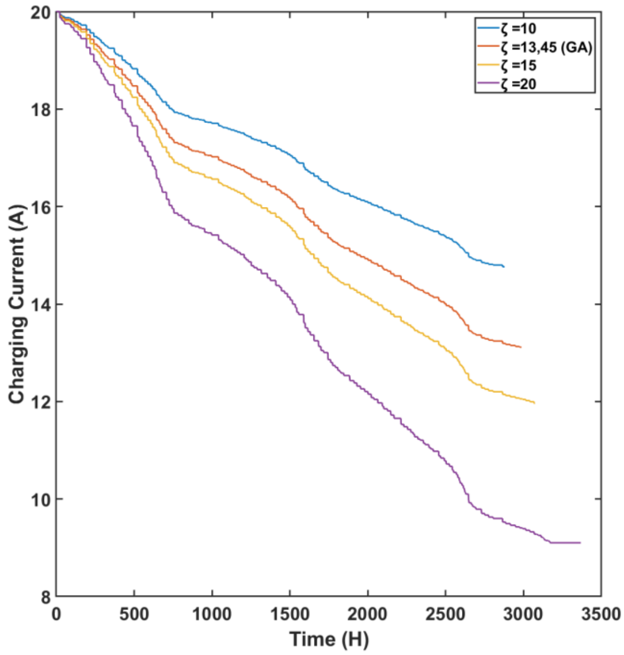

Fig. 8 Charging currents under different weighting parameters for constant load condition test

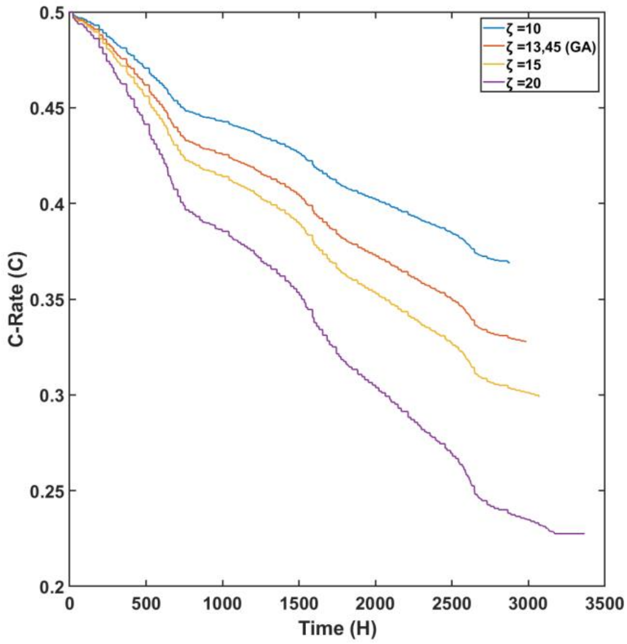

Fig. 9 C-Rate values under different weighting parameters for constant load condition test

Figure 10 compares the energy amounts obtained from the battery tested under constant load and different weighting parameters. When the weighting parameter is set as ζ =10, 749.0271 kWh of energy can be extracted from the battery for 2878.5 hours. However, the charging time increases by 249.3 hours compared to the system controlled with a constant C-Rate. An increase of 9.41% is observed in the energy that can be obtained. When the parameter is updated to ζ =13.45, which is the optimal ζ of the genetic algorithm, the total charging time increases by 343.3 hours, but the amount of energy that can be obtained increases by 14.18% to 781.663 kWh. When the weighting parameter is doubled compared to the first case (ζ =20), the charging time increases by 738.4 hours, and the amount of energy that can be obtained is measured as 874.926 kWh with an increase of 27.8%.

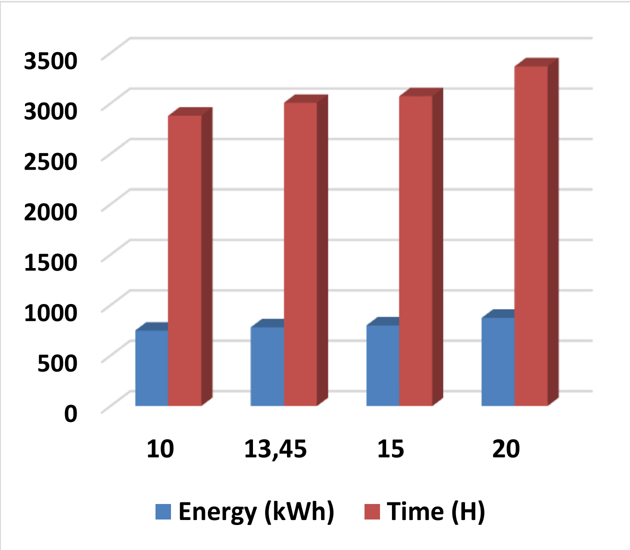

Fig. 10 Energy comparison of different weighting parameters for constant load condition test

4.3. Case Study II: Variable Load Profile

The second simulation study used a load requiring variable discharge with the profile in Figure 11. While preparing the profile, sudden charging requirements were created, and stationary states were added and designed to use different discharge currents in the whole process. The battery was tested at various temperatures during its lifetime. A separate C-Rate was determined for each temperature cycle using the proposed approach. Using four different ζ parameters, the variation of the charging current values obtained is given in Fig. 12, and the corresponding C-Rate values are presented in Fig. 13.

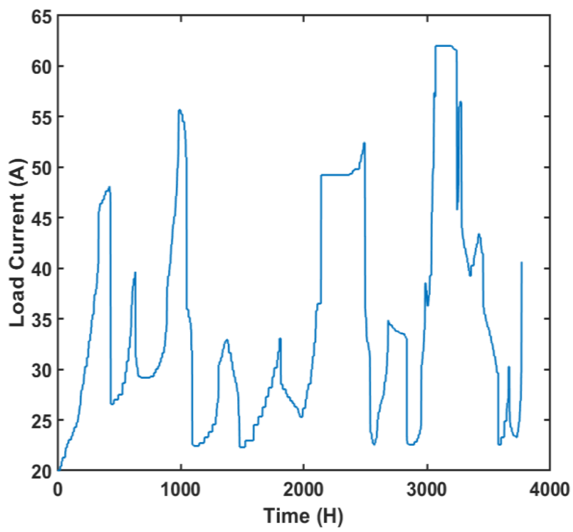

Fig. 11 Load current profile for variable load condition test

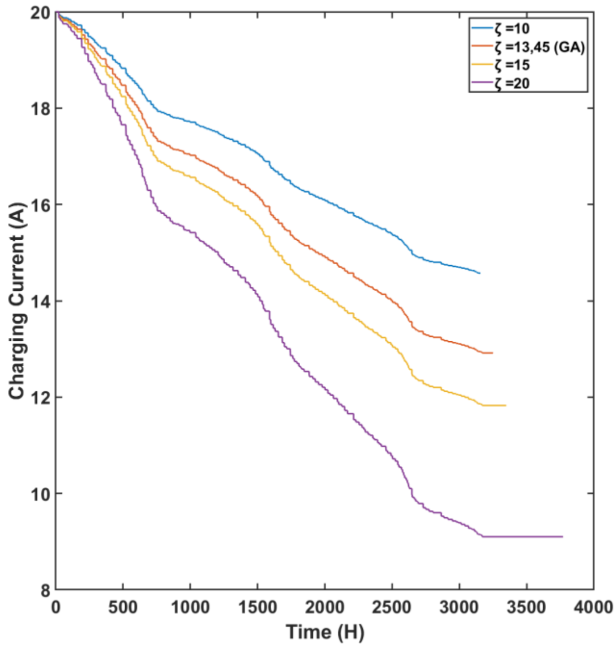

Fig. 12 Charging currents under different weighting parameters for variable load condition test

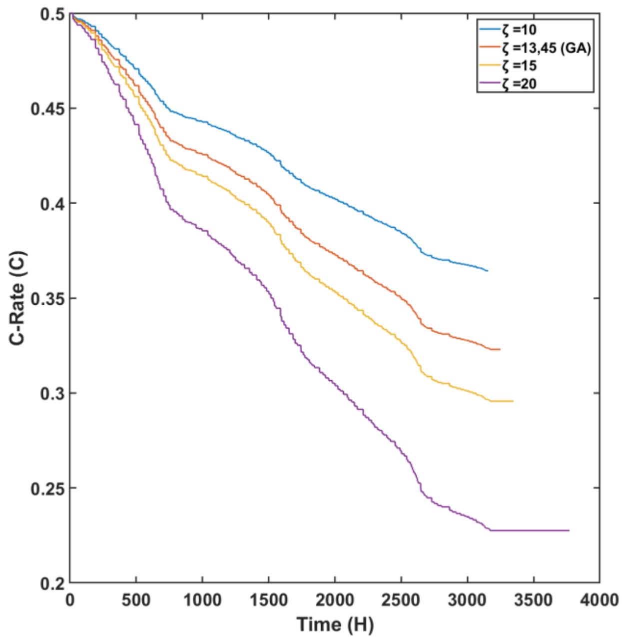

Fig. 13 C-Rate values under different weighting parameters for constant load condition test

Figure 14 compares the energy amounts obtained from the battery tested under variable load profiles under different weighting parameters. When the weighting parameter is set as ζ =10, 824.341 kWh of energy can be extracted from the battery for 3156.2 hours. However, the charging time increases by 241.6 hours compared to the system controlled with a constant C-Rate. An increase of 8.14% is observed in the energy that can be obtained. When the parameter is updated to ζ =13.45, which is the optimal ζ of the genetic algorithm, the total charging time increases by 338.6 hours, but the amount of energy that can be obtained increases by 11.84% to 852,482 kWh. When the weighting parameter is doubled compared to the first case (ζ =20), the charging time increases by 738.4 hours, and the amount of energy that can be obtained is measured as 983.606 kWh with an increase of 29.04%.

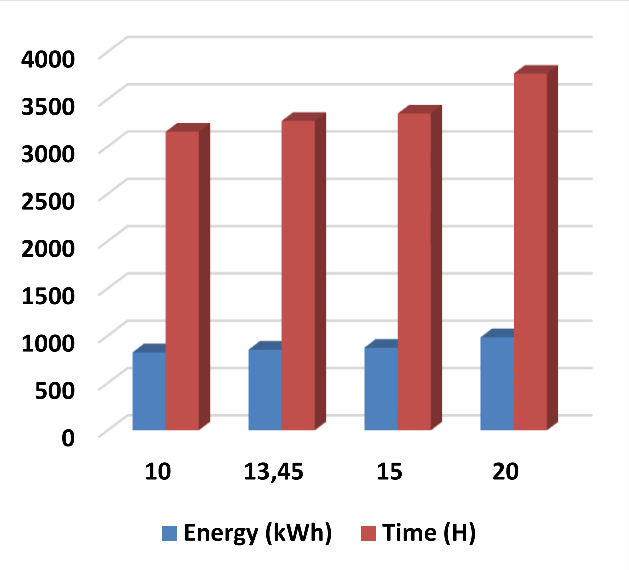

Fig. 14 Energy comparison of different weighting parameters for variable load condition test

In the proposed approach, it is seen that if the weighting parameter is selected more widely, the energy that can be drawn from the battery in the long term may increase, but the charging time in single cycles will increase at the same rate. There is an inverse relationship between the increase in the weighting parameter and the charging current, and as one increases, the other decreases. The proposed approach creates flexibility for the designer in this regard, and it is foreseen that the most appropriate weighting parameter will be selected due to the cost-benefit analysis. Table 2 shows the comparative results of all simulation studies.

TABLE 2 Comparison of the test profiles in terms of Energy and Time

Load	ζ	Energy (kWh)	Time (H)
Constant Load Profile	0 (Constant C-Rate)	684.5776	2629.2
	10	749.0271	2878.5
	13.45 (GA)	781.663	3005.6
	15	798.809	3072.4
	20	874.926	3367.6
Variable Load Profile	0 (Constant C-Rate)	762.224	2914.6
	10	824.341	3156.2
	13.45 (GA)	852.482	3270.1
	15	873.641	3348.4
	20	983.606	3770.4

5. CONCLUSIONS

In this study, an adaptive battery management system based on temperature and charging rate is developed for lithium-based battery systems (LBS). LBS, an electrochemical storage technology, can offer high power and high energy density at the same time. Thus, it can respond to continuous power needs and meet sudden power demands. The temperature harms LBS chemistry, and it is crucial to use LBS in high-temperature environments with unique management systems for its long life.

In the proposed approach, a differential relationship between ambient temperature and charging rate is established, and the aim is to update the charging rate as the temperature changes. In this way, two conditions likely to cause thermal stress on the LBS are prevented from affecting the LBS simultaneously. With the proposed approach, the life of the battery is extended, and the environmental waste generation is reduced by extending the battery replacement time. The genetic algorithm optimized the ζ parameter used for balancing in the study.

The study was carried out under two different load profiles. Firstly, in the simulation studies performed under constant load, it was observed that 14.18% more energy could be obtained compared to the EMS using constant charging speed using the optimal ζ, obtained by genetic algorithm. On the other hand, it was observed that the amount of energy that can be obtained can be increased by 27.8% by using the ζ =20, although it causes the charging time to increase. Similarly, in simulation studies under variable load current, it is observed that an 11.84% energy increase is obtained when the weighting parameter ζ =13.84 is selected. In comparison, a 29.04% energy increase is observed when ζ =20 is selected.

The obtained findings reveal the success of the proposed battery management system and ensure the safe operation of the LBS by protecting it from temperature-related hazards while healthily extending the battery life.

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