

An Adaptive Energy Management Approach for Battery-Supercapacitor Hybrid Energy Storage System

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Abstract Energy storage systems (ESS) are indispensable in daily life and have two types that can offer high energy and high power density. Hybrid energy storage systems (HESS) are obtained by combining two or more energy storage units to benefit both types. Energy management systems (EMS) are essential in ensuring HESS's reliability, high performance, and efficiency. One of the most critical parameters for EMS is the battery state of health (SoH). Continuous monitoring of the SoH provides essential information regarding the system's status, detects unusual performance degradations and enables planned maintenance, prevents system failures, helps keep efficiency at a consistently high level, and helps ensure energy security by reducing downtime. The SoH parameter depends on parameters such as Depth of Discharge (DoD), charge and discharge rate (C-Rate), and temperature. Optimal values of these parameters directly affect the lifetime and operating performance of the battery. The proposed Adaptive Energy Management System (AEMS) uses the SoH parameter of the battery as the control input. It provides optimal control by dynamically updating the C-Rate and DoD parameters. In addition, the supercapacitor integrated into the system with filter-based power separation prevents deep discharge of the batteries. Under the proposed AEMS control, HESS has been observed to generate 6.31% more energy than a system relying solely on batteries. This beneficial relationship between supercapacitors and batteries efficiently managed by AEMS opens new possibilities for advanced energy management in applications ranging from electric vehicles to renewable energy storage systems.

Key words: Lithium batteries, Energy management systems, Renewable energy, Hybrid Energy storage, Supercapacitor

1. INTRODUCTION

The ever-increasing population, industrial developments, and rapid technological developments increase the energy needed [1]. The negative environmental impacts of fossil fuels, the most widely used energy source in today's world, and the fact that they cause climate change make it necessary to turn to alternative energy sources. Investments in renewable energy sources such as wind, biomass, solar, and hydroelectricity, which have low negative impact on the environment, continue to increase [2], [3], [4]. Although energy produced based on the cycle of nature is sustainable, it has disadvantages in terms of continuity. Solar power plants cannot produce at night and operate with low efficiency on cloudy days. Similarly, wind power plants can only produce when the wind blows at a specific interval [5], [6], [7]. Considering energy is a constant need, renewable energy sources are integrated with energy storage systems (ESS) to meet this need. While ESSs charge during the periods when the RESs generate energy, they feed the system with the energy they store during the hours when production stops, ensuring the reliability and continuity of the energy supply.

ESSs can be divided into two categories in terms of density: energy and power density. High-energy density storage

systems store large amounts of energy and realize long-term energy release. Storage units such as lithium-based batteries and fuel cells are considered in this class. Although these systems can store energy densely, they have the disadvantage of releasing energy quickly and in large quantities. On the other hand, high-power density energy storage systems allow for the instantaneous release of energy. Supercapacitors and flywheel systems are examples of this storage technique. Both systems serve different purposes and needs [8]. Hybrid energy storage systems (HESS) have been developed to utilize the advantages of both systems. Thanks to integrating two technologies, HESS balances energy and power needs, providing long-term energy and meeting instantaneous power needs. In addition, applications requiring instantaneous power prevent stress on the storage unit, which has a high energy density and extends the cycle life [9]. There are many hybrid energy storage options in the literature [10], [11], [12], [13]. It is also widespread to use batteries, the most widely used high energy density storage unit [14], in hybrid with supercapacitors, the most commonly used high power density storage unit [15], [16].

An energy management system (EMS) must control hybrid storage systems' efficiency and high-performance operation [17]. EMSs are essential to control, effectively monitor, and optimize energy consumption by monitoring and analyzing various parameters. EMSs can use parameters directly

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measured by sensors, such as current, voltage, and temperature [18]. Still, for high performance, they also need battery parameters such as state of charge (SoC), state of health (SoH), charge-discharge rate (C-Rate), and depth of discharge (DoD), which can be obtained indirectly by estimation or prediction [19], [20].

One of the most critical parameters affecting the reliability and performance of ESS is SoH. With SoH monitoring, which can be estimated from the data of the ESS obtained through sensors, it is possible to determine the instantaneous status of the ESS and the approximate stage of its life in general use and to identify potential problems in advance. It can also detect unusual drops in performance, enable planned maintenance, prevent system failures, keep efficiency at a constant high level, and ensure energy security by reducing downtime. The SoH parameter can be used as a performance and success indicator for EMSs, as well as a part of an algorithm that directs the operation of the EMS by using it as input. Using the SoH parameter as an EMS input, which provides information considering the whole life of the batteries, plays a crucial role in developing strategies to increase components' lifetime and realize longevity perspective [21].

Another essential element that can be used in ESSs is the parameter that determines the charge and discharge rates, also called C-Rate. C-Rate is critical for evaluating cell and battery performance in energy storage systems [22]. C-Rate is a rate that expresses the charge or discharge rate of a cell or battery relative to its nominal capacity. This parameter is critical in how energy management systems monitor, control, and optimize battery performance. The C-Rate of batteries indicates how quickly they can store or release energy [23]. The EMS uses this information to determine how the battery can respond to sudden energy demands and ensure optimum performance. This parameter can also control the current value at which the battery will be charged. By using the C-Rate parameter as a control argument, EMSs increase battery life and performance by providing charging and discharging at the optimum value. This way, battery costs are reduced, and system security is increased [24], [25], [26].

DoD is another critical element used in energy management systems [27], [28]. DoD, which can also be called useful capacity, is a parameter that shows how much of the instantaneous maximum capacity of the battery is used. It indicates how much the battery can be discharged in each cycle and is used to determine the minimum value of the SoC parameter. The determination of the DoD level is shaped by system and user needs. A low DoD level allows the battery to be used for a shorter period, extending battery life, while high DoD levels provide more energy output. However, as the battery is exposed to more cycles, the cycle life decreases in parallel [29]. Keeping DoD at an optimal level is essential for stabilizing battery costs and increasing the economic efficiency of energy storage systems [30], [31]. The use of optimal DoD levels in EMSs is of great importance in terms of both long-term cost savings and optimizing system performance [32], [33], [34].

The literature has shown significant interest in exploring the relationship between SoH and DoD within EMS. In [35], an experimental investigation to understand how different DoD

values impact battery aging. This research revealed some critical insights. The study found that the most efficient operational practice involves varying the DoD based on the SoH of the battery. Specifically, it was determined that operating at 70% DoD is most efficient when the battery's SoH is between 90% and 100%.

In contrast, when the SoH is between 80% and 90%, adjusting the DoD to 60% has better results. This dynamic approach, as opposed to a static 60% DoD usage, was shown to significantly improve the performance of the EMS, particularly in terms of the amount of energy effectively extracted from the battery. Despite the success of this study, it also highlighted a limitation in the current scope of EMS design. The research only incorporated two distinct DoD values into the EMS, thus limiting the system's adaptability. This limitation suggests that there is potential for further refinement in EMS design. By incorporating a broader range of DoD values and perhaps integrating more nuanced SoH parameters, EMSs could achieve even higher efficiency and battery longevity. Such advancements would improve energy extraction and contribute to battery-based energy storage systems' sustainability and cost-effectiveness.

In another notable study, referenced as [36] in the literature, researchers employed a non-dominated sorting genetic algorithm (NSGA) to conduct aging tests for batteries at varying DoD levels. This advanced algorithmic approach enabled the determination of an optimal DoD value, which was found to be 70%. The study meticulously calculated the energy cost of this specific DoD level, pinpointing it at \$0.20456 per kilowatt when maintaining a fixed 70% DoD. While the study did not delve into the development of an adaptive EMS structure, it marked a significant advancement in optimizing the relationship between DoD and the SoH of batteries. This optimization led to noticeable improvements in system performance. However, exploring more complex EMS designs could further expand the research. For instance, integrating a dynamic, adaptive system that adjusts the DoD based on real-time SoH data and other operational parameters could further enhance efficiency and cost-effectiveness. Moreover, advanced algorithms like NSGA could be explored in more depth. By applying these algorithms in a broader context, including real-time decision-making processes in EMS, the potential for even more nuanced and effective energy management strategies emerges. This could lead to significant battery technology and energy management breakthroughs, offering more sustainable, efficient, and economically viable energy storage and utilization solutions. In a significant contribution to the field, documented as a study [37], researchers developed an EMS where the DoD parameter was optimally determined within a predefined range. This innovative design incorporated two critical cost functions: battery degradation and energy loss throughout the battery's life. Battery degradation was quantitatively assessed through the cost of battery replacement and an Estimated Battery Life (EBL) model. The study strategically established a range for DoD values, within which the most optimal DoD was selected based on the system's capacity. This approach of using an optimal DoD, as opposed to a fixed one, yielded a longer EBL, showcasing the effectiveness of the design in enhancing battery longevity. However, it's important to note

that this study set the DoD value based on the system's initial conditions and maintained it consistently throughout. This means the system lacked adaptability, as there was no provision for modifying the DoD value in response to changing operational conditions or battery health. While practical under controlled conditions, the study's approach points to a broader challenge in battery management: the need for adaptability in diverse and changing environments. This is particularly relevant for electric vehicles and portable devices, where battery performance can vary significantly due to environmental factors, usage patterns, and operational demands. While studies like [37] have made strides in extending battery life under specific, controlled conditions, they highlight a gap in addressing variable real-world scenarios. Future research could focus on developing more dynamic, adaptive EMS designs. These systems would optimize DoD based on initial conditions and continuously adjust it in response to real-time data on battery health, environmental factors, and usage patterns. Such advancements could lead to more robust, efficient, and sustainable battery management solutions catering to the diverse needs of modern technology and transportation systems.

The proposed adaptive energy management system (AEMS) dynamically changes DoD and C-Rate parameters. The most important parameter of this study is the battery health status parameter that enables this dynamic change. Integrating the SoH parameter into the EMS allows the battery to adapt to health conditions throughout its operational lifetime. The proposed work uses differential equations based on an analytical approach adapted to the SoH parameter, allowing the DoD and C-Rate parameters to be updated appropriately for each battery cycle. This approach allows for more efficient energy consumption, leading to longer lifetimes. The EMS design is tested through simulation studies using Matlab/Simulink. These simulations have demonstrated the proposed EMS's clear superiority over battery-only systems using fixed DoD and C-Rate values and the battery-only system managed using AEMS, showing significant improvements in battery life and system efficiency.

Another important aspect of this study is the inclusion of a supercapacitor within the system. The supercapacitor is crucial for alleviating abrupt discharges in the battery, which negatively affect its health. By leveling out these sharp discharge events, the supercapacitor not only aids in preserving the battery's lifespan but also boosts the system's overall dependability and efficiency. This integrated strategy, which combines sophisticated algorithmic control with a supercapacitor, marks a notable advancement in battery management technologies. It prolongs the battery's usable life and creates more robust and efficient energy systems. This approach could significantly change energy management across various sectors, including electric vehicles and large-scale renewable energy storage, offering a more reliable, sustainable, and cost-efficient solution.

The main contributions of this paper as follows:

1. Designing a new adaptive energy management system for battery-supercapacitor hybrid energy storage systems in which the battery SoH parameter is used as input and the C-Rate and DoD parameters are

continuously updated accordingly to extend the lifetime of the batteries.

2. With the proposed differential approach, DoD and C-Rate parameters can be updated with weighting parameters throughout the operating life of the system so that the battery-supercapacitor hybrid energy storage system can adapt to challenging conditions.

This paper is organized as follows: Firstly, the aging model of lithium-based batteries is explained. Then, the mathematical expression of the supercapacitor is given, and differential equations and justifications for the proposed study are described. Then, the flowchart of the proposed study is presented. Then, the impact of the SoH parameter-based energy management and the supercapacitor used for the peak power demands on the battery's cycle life are shown with simulation studies. Finally, the AEMS simulation studies are analyzed, demonstrating its superiority.

2. MATERIAL and METHODS

An energy management system design is realized based on the battery aging model for the proposed study. A hybrid energy storage system is created with a supercapacitor, and filter-based power sharing is realized.

2.1. Lithium-Ion Battery Aging Model

SoH of a battery is calculated as the percentage ratio of the current capacity of the battery Q_n to its initial capacity Q_{BOL} , as demonstrated in Equation 1.

$$\text{SoH}(\%) = \left(\frac{Q_n}{Q_{BOL}} \right) \times 100 \quad (1)$$

As expressed in [38] for the lithium-ion battery, the effect of aging on the battery capacity and internal resistance is given as follows;

$$Q(n) = \begin{cases} Q_{BOL} - \varepsilon(n) \cdot (Q_{BOL} - Q_{EOL}) & \text{if } k/2 \neq 0 \\ Q(n-1) & \text{otherwise} \end{cases} \quad (2)$$

$$R(n) = \begin{cases} R_{BOL} + \varepsilon(n) \cdot (R_{EOL} - R_{BOL}) & \text{if } k/2 \neq 0 \\ R(n-1) & \text{otherwise} \end{cases} \quad (3)$$

$$n = kT_h \quad (k = 1, 2, 3 \dots \infty) \quad (4)$$

where, T_h represents the time duration of half a cycle, measured in seconds, Q_{BOL} represents the battery's maximum capacity in Ampere-hours (Ah) when it is new, at the beginning of its life (BOL), and under normal ambient temperature conditions, Q_{EOL} represents the battery's maximum capacity in Ah at the end of its life (EOL), and this measurement is taken at the nominal ambient temperature, R_{BOL} stands for the internal resistance of the battery, measured in ohms at the BOL and under the rated ambient temperature conditions., R_{EOL} is the internal battery resistance, measured in ohms, at EOL and under the rated ambient temperature conditions, ε represents the battery's aging factor, which assumes zero values at the BOL and one at the EOL.

DoD is a crucial metric for measuring a battery's usage and efficiency. It measures the proportion of energy withdrawn from a battery in a discharge cycle, indicating how much of the battery's total capacity has been used. Represented as a percentage, DoD provides essential insights for optimizing battery performance and lifespan. It is integral to battery management, influencing efficiency and system functionality. DoD is mathematically linked to the SoC, which reflects the current charge level as a percentage of maximum capacity. To enhance energy use and prolong battery life, DoD and SoC are vital for effective battery management in various applications, including electric vehicles and renewable energy systems.

$$\Delta SoC(k) = SoC(k) - SoC(k-1) \quad (5)$$

$$DOD(n) = 1 - SoC(k) \text{ if } \Delta SoC(k) \neq \text{sign} \Delta SoC(k-1) \quad (6)$$

The effect of DoD on the aging factor as follows

$$DOD_{ef} = \left(2 - \frac{DOD(n-2) + DOD(n)}{DOD(n-1)} \right) \quad (7)$$

and also, ε can be shown as;

$$\varepsilon(n) = \begin{cases} \varepsilon(n-1) + \frac{0.5}{N(n-1)} DOD_{ef} & \text{if } k/2 \neq 0 \\ \varepsilon(n-1) & \text{otherwise} \end{cases} \quad (8)$$

Let's express the average charge and discharge currents during a half-cycle, considering the exponential factor that varies based on these charge and discharge currents.

$$I_{ch-dis} = (I_{dis_ave}(n))^{-\gamma_1} (I_{ch_ave}(n))^{-\gamma_2} \quad (9)$$

Then, N is the maximum number of cycles, and the following equation can express it.

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

where H represents the constant related to the number of cycles, ξ is the DoD's exponent factor, ψ is the rate constant for the cycle number in Arrhenius-like models, I_{dis_ave} represents the average discharge current throughout half a cycle, I_{ch_ave} signifies the average charge current throughout half a cycle, γ_1 represents the exponent factor for the discharge current, while γ_2 represents the exponent factor for the charge current.

2.2. Supercapacitor Model

In our past study, the supercapacitor was modeled using the Debye polarization equivalent circuit [16]. This model was

used because of its simplicity and uncomplicated mathematical theory. The Debye polarization equivalent circuit shown in fig. 1 includes the leakage current and adsorption capacity parameters.

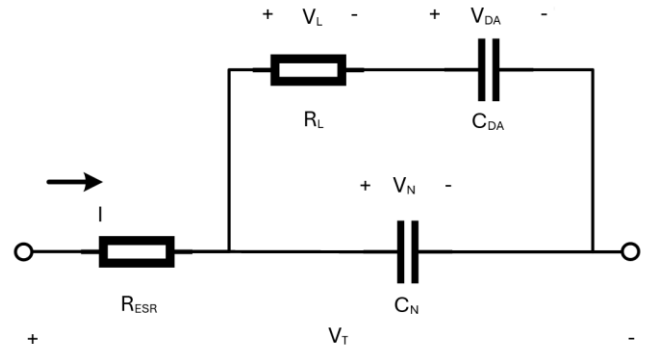


Fig. 1 Debye polarization equivalent circuit model

The electrical behavior of the Debye polarization equivalent circuit model can be expressed as following equations:

$$\frac{dV_{DA}}{dt} = \frac{1}{R_L C_{DA}} V_{DA} + \frac{1}{R_L C_{DA}} V_N \quad (11)$$

$$\frac{dV_N}{dt} = \frac{1}{R_L C_N} V_{DA} + \frac{1}{R_L C_N} V_N - \frac{1}{C_N} I \quad (12)$$

$$V_T = V_N - I R_{ESR} \quad (13)$$

where R_{ESR} is the equivalent series resistor, R_L is the leakage current resistance, C_{DA} is the Debye adsorption capacitance, and C_N is the nominal capacitance.

2.3. Proposed Energy Management System for Hybrid Energy Storage System

The AEMS introduced in this research offers a dynamic method for managing battery performance, emphasizing the adjustment of DoD and C-Rate parameters in reaction to the battery's SoH. According to Equation 8, there is a direct correlation between DoD and the aging factor of the battery. This correlation acknowledges that varying discharge depths lead to different levels of wear and aging in the battery. Consequently, tailoring the DoD to align with the battery's current health is crucial for prolonging its service life. Additionally, the impact of the C-Rate value is analyzed in equations 9 and 10, highlighting its direct relationship with the number of cycles and its indirect ties with the aging factor through cycle count. Equations 19 and 20 provide the proposed hypotheses and mathematical approximations that establish the x and y variable parameters of AEMS in terms of the aging factor to complete the adaptive approach. In essence, this adaptive approach signifies a shift from fixed battery management strategies to ones that are dynamic and responsive to the battery's health. By linking DoD and C-Rate directly to the aging factor with x and y weighting parameters, AEMS optimizes energy use while maintaining battery health, resulting in longer life and more efficient battery performance. The differential theorem is based on the hypothesis that DoD and C-Rate should also decrease concerning the capacity of the battery, thus slowing down the aging effect. Optimization

methods can be used to select weighting parameters, which can also be selected according to user needs and demands. Equation 1 is rewritten to give equation 14.

$$\left(Q_n = \frac{\text{SoH}(\%) * Q_{\text{BOL}}}{100} \right) \quad (14)$$

Substituted in Equation 2;

$$\frac{\text{SoH}(\%) * Q_{\text{BOL}}}{100} = Q_{\text{BOL}} - \varepsilon(n)(Q_{\text{BOL}} - Q_{\text{EOL}}) \quad (15)$$

is achieved. Batteries are considered dead if their capacity drops to 80%. In this case, Q_{EOL} value can be accepted as 80% of Q_{BOL} value. If equation 15 is rewritten under these conditions,

$$\frac{\text{SoH}(\%) * Q_{\text{BOL}}}{100} = Q_{\text{BOL}} - \varepsilon(n)(Q_{\text{BOL}} - 0.8 * Q_{\text{BOL}}) \quad (16)$$

If the equation is modified,

$$\text{SoH}(\%) = \frac{100 * Q_{\text{BOL}}(1 - 0.2 * \varepsilon(n))}{Q_{\text{BOL}}} \quad (17)$$

$$\varepsilon(n) = \frac{100 - \text{SoH}(\%)}{20} \quad (18)$$

is obtained. The analytical connection between an aging factor and a battery's remaining life is discussed here. Equation 8 shows that DoD and C-Rate remain consistent throughout the battery's lifespan. Furthermore, as the battery ages, its capacity diminishes. This reduction in capacity significantly affects systems that operate with a constant DoD. Additionally, Equation 10 reveals how the charging speed influences the number of battery cycles. Consequently, the aging factor is also indirectly affected by the charging rate.

The proposed AEMS with variable DoD and C-Rate reduces the operating capacity and charging rate in a controlled manner and aims to minimize the aging effect. For this purpose, a differential equation that correlates the DoD and charging current value with the SoH of the battery and re-evaluates it according to the aging factor is created and given in equations 19-20. Using such differential equations within the AEMS allows for a dynamic and intelligent approach to battery management. The system can optimize battery performance by continuously monitoring and adjusting DoD and charging current in response to the aging factor while mitigating the degradation typically associated with battery cycling.

$$\text{DoD}_{\text{max}}(n) = \text{DoD}_{\text{max}}(n-1) - \frac{\varepsilon(n)}{x * \text{SoH}(\%)} \quad (19)$$

$$I_{\text{ch}}(n) = I_{\text{ch}}(n-1) - \frac{\varepsilon(n)}{y * \text{SoH}(\%)} \quad (20)$$

The supercapacitor is integrated into the system to extend the battery life, as shown in fig. 2. With a low-pass filter, the power demanded is optimally shared between the supercapacitor and the battery.

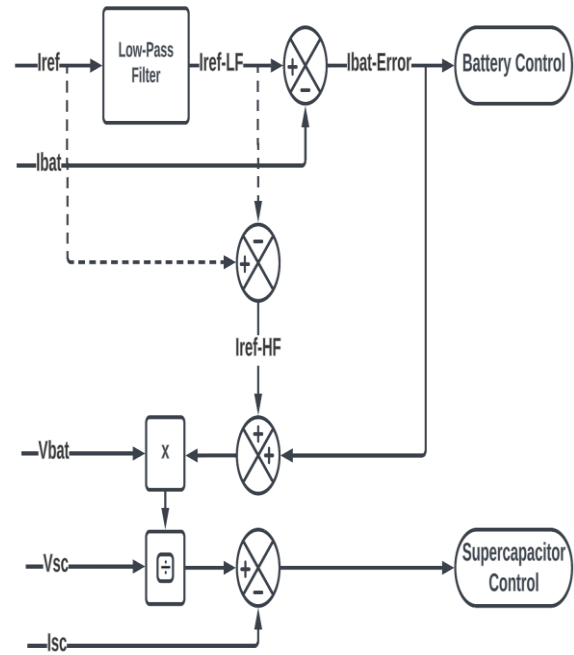


Fig. 2 HESS Power Share Strategy

Total reference current (I_{ref}) needs to be adjusted to counteract any voltage fluctuations, thereby ensuring stability in power levels. I_{ref} is then split into the low-frequency component (LFC) and the high-frequency component (HFC). Firstly, I_{ref} goes through a low pass filter, separating the LFC ($I_{\text{ref-LF}}$), which becomes the reference for the battery loop. This loop adjusts for the low-frequency deviations in power. Meanwhile, the Supercapacitor control loop manages the HFC of the reference current ($I_{\text{ref-HF}}$). The reference for this loop, $I_{\text{SC-ref}}$, is determined using $I_{\text{ref-HF}}$ combined with the battery error current ($I_{\text{bat-error}}$), which is the difference between the reference current and the battery current.

AEMS described in this study operates on a dynamic algorithm guided by user-defined weighting parameters, denoted as x and y , designed to be optimized according to the system's specific characteristics and usage requirements. The primary objective is to achieve optimal battery usage by continually adjusting DoD and C-Rate values based on these user-defined design parameters. Figure 3 provides a flowchart illustrating the AEMS process.

In summary, the AEMS algorithm presents a dynamic and adaptive approach to battery management, allowing users to tailor DoD and C-Rate settings to their specific needs. The hybrid structure created with the supercapacitor added to the system minimizes the damage to the chemical structure of the battery by preventing sudden current draws. The algorithm optimizes energy utilization, extends battery life, and ensures efficient operation by continuously monitoring and adjusting these parameters based on the battery's state. It is a valuable tool in various applications requiring reliable and sustainable energy storage solutions.

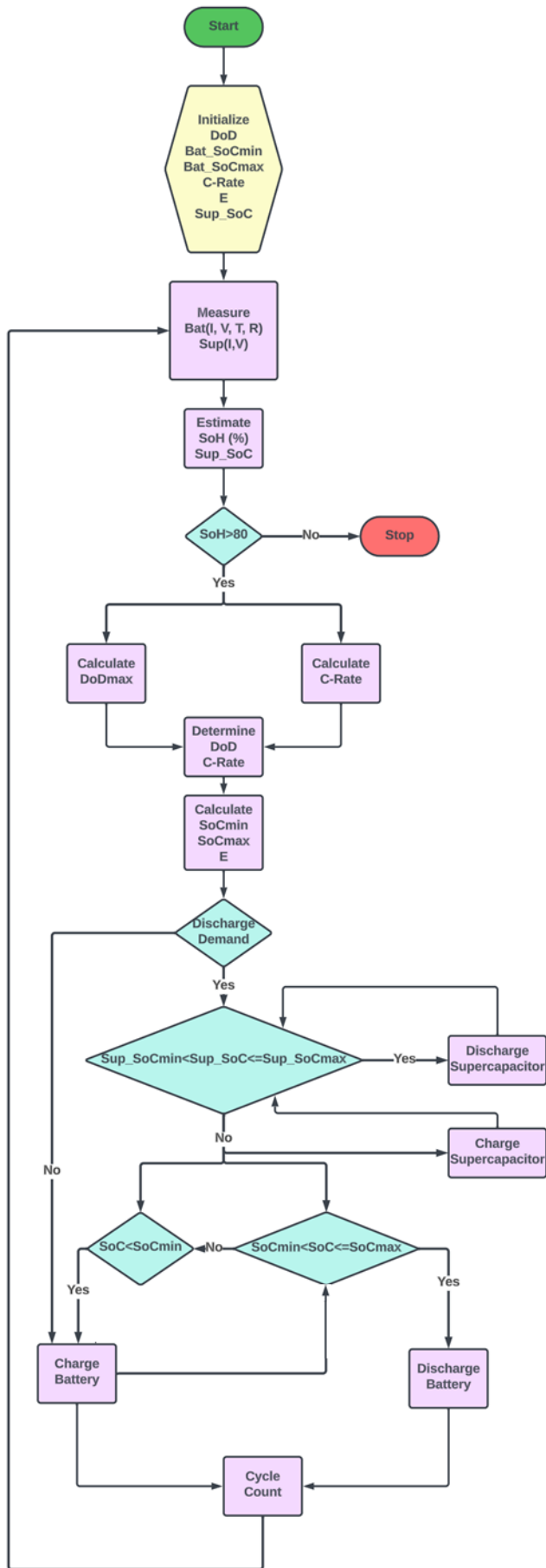


Fig. 3 Proposed AEMS Flowchart

3. SIMULATION STUDY

Simulink diagram was established using Matlab/Simulink for simulation studies, which is given in fig. 4. The simulation diagram consists of 7 parts: battery block, supercapacitor block and their control blocks, block containing the proposed algorithm, power calculation block and termination block. With the proposed algorithm, control signals are generated based on the power calculations of the system, whose operating limits are determined separately in each cycle, and the data are monitored instantaneously with the monitoring blocks in the battery and supercapacitor blocks. The termination block continuously monitors the battery capacity and terminates the system when it drops below 80%. Information about the supercapacitor used to support the battery, the primary storage unit, is given in table 1. The supercapacitor block formed by connecting 5 supercapacitors in parallel with the data of the BCAP0600 P270 S18 model produced by Maxwell was used.

TABLE 1 Supercapacitor parameters

Parameter	Value
Rated Capacitance	600 F
Rated Voltage	2.7 V
Surge Voltage	12.95 V
Leakage Current	1.5 mA
Peak Current	280 A
Continuous Current	32 A _{RMS}
Equivalent DC Resistance	8.9 mΩ
Operating Temperature	-40 °C to +85 °C
Projected Cycle Life	>1000000
Projected Life Time	10 Years
High-Temperature Life Time	3000 Hours
Shelf Life	4 Years
Mass	95 g (per supercapacitor)
Thermal Resistance	5 °C/W
Thermal Capacitance	170 J/°C

Powerbrick+ LiFEPO4 battery data was used as the primary storage unit, and datasheet information is given in table 2.

TABLE 2 Battery 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
DoD	Variable
Stored Energy	512 Wh
Mass	5.25 kg
Max Discharge	2C

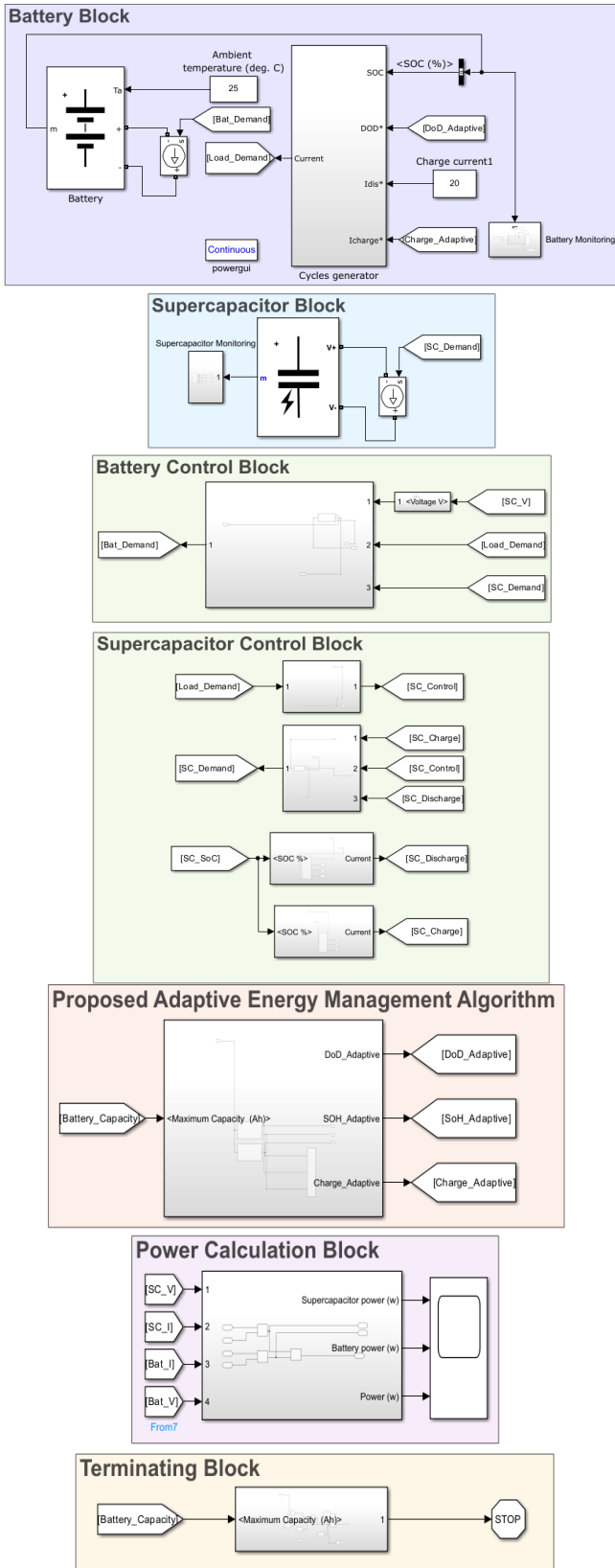


Fig. 4 Simulation diagram of the proposed AEMS

First, an operating scenario under a constant temperature of 25 °C was prepared to understand how the battery responds to different C-Rate and DoD parameters regarding aging. C-Rate and DoD parameters were analyzed separately. First, the C-

Rate parameter was kept constant at 0.5C, and the total energy available from the battery was calculated for 60%, 70%, 80%, 90%, and 100% DoD values. Then, the DoD parameter was kept constant at 80%, and energy calculations were performed for C-Rate values of 0.25C, 0.5C, 1C, and 1.5C. In the simulation study where the DoD effect is examined in Table 3, it is seen that at values of 80% and above, also known as deep discharge, the energy that can be withdrawn from the battery decreases significantly.

TABLE 3 DoD effect on the battery life

DoD	C-Rate	Time (Hour)	Cycle	Energy (kWh)
60	0.5	6561.22	3084	1729.6
70	0.5	6135.57	2476	1612.74
80	0.5	5802.53	2050	1519.81
90	0.5	5520.73	1734	1438.97
100	0.5	5305.64	1484	1372.18

Figure 5 also shows how the battery SoH parameter changes with time and cycle under different DoD parameters. As can be seen, there is an inverse relationship between the DoD parameter and the battery aging, and as the DoD increases, the battery reaches its end of life earlier.

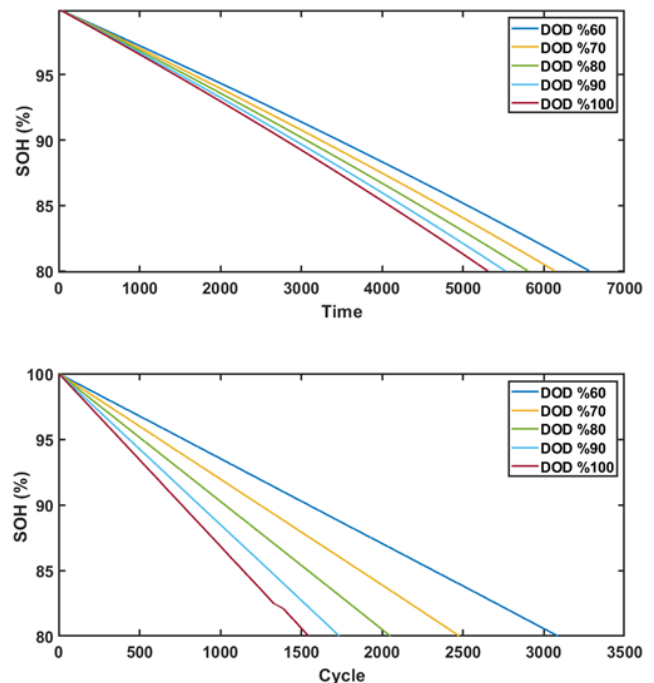


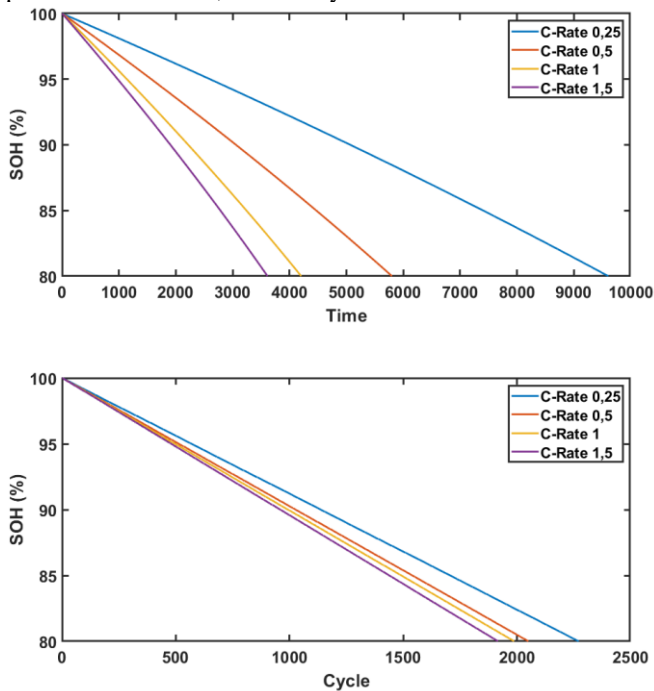
Fig. 5 Effect of DoD on the SoH

Table 4 shows how vital the C-Rate parameter is for the battery's life. It is seen that the high current values used to save time during charging cause significant damage to the battery chemistry in long-term use and significantly reduce the total amount of energy that can be drawn. As a result, DoD and C-Rate parameters have an inverse relationship with battery life. Dynamically optimizing both parameters can directly contribute to the battery life and is necessary to maximize the energy drawn.

TABLE 4 C-Rate effect on the battery life

C-Rate	DoD	Time (Hour)	Cycle	Energy (kWh)
0,25	80	9608.09	2271	2502.24
0.5	80	5802.53	2050	1519.81
1	80	4205.25	1987	1114.85
1,5	80	3612.40	1916	994.75

Similarly, fig. 6 shows how the battery C-Rate parameter changes with time and cycle under different DoD parameters. In the simulation setup prepared by considering the factory data of the battery used, it did not exceed 1.5C. As the C-Rate parameter increases, the battery finishes its life earlier.

**Fig. 6** Effect of C-Rate on the SoH

In the proposed study, two approaches are combined under a single algorithm to extend the battery's lifetime, which is used as the primary energy source, and the total energy that can be drawn. Firstly, to prevent all energy from being withdrawn directly from the battery when the system enters the discharge state, it aims to maintain the battery chemistry for a more extended period with supercapacitor support. With the hybridization realized using active topology, both the supercapacitor and the battery are kept under control, and the energy required by the system can be provided uninterruptedly and most efficiently. Secondly, the proposed study adaptively controls the hybridized energy storage system. AEMS has been implemented to use the SoH parameter as a control variable and optimize the DoD and C-Rate parameters in line with this parameter. In the design criteria, the DoD parameter should not fall below 60% and should not exceed 80%. This is because DoD values of 80% and above cause deep discharges and cause irreversible degradation of the battery chemistry. In addition, the 60% DoD value aims to use the battery with efficient capacity and longer life. The performance criterion considered in the

AEMS design is that the amount of energy that the system under the control of the AEMS should not fall below the amount of energy that can be drawn with a constant 60% DoD. In this way, it aims to achieve an optimal balance between battery health, longevity, and total energy drawn.

3.1. AEMS Weighting Parameter Determination

To meet the design criteria, the weighting parameters x and y will enable dynamic optimization of DoD and C-Rate parameters. The mathematical expression of the energy management system given in equations 19 and 20 is introduced. As shown in fig. 7, the maximum amount of energy that can be extracted from the battery system in hybrid energy systems operating under different x and y parameters has been analyzed. A set of design criteria, defined with all trade-offs in mind, has shaped the design of the proposed AEMS. These criteria were developed to optimize the performance and durability of the battery. Foremost among these criteria is the decision that DoD should never drop below 60%. This threshold was chosen to make the most efficient use of the battery's capacity while avoiding deep discharges that could damage the health of the battery. It is also stipulated that the DoD should not exceed 80% to prevent over-discharge, a condition that can significantly reduce the battery's life.

Furthermore, the design criterion was set to ensure that the energy output from the AEMS system is consistently equal to or more than the energy output of a system designed with a constant 60% DoD. Finally, the expected lifetime of the battery, which is required to be no less than a system designed with a constant 60% DoD, is also a critical consideration. These design conditions emphasize the importance of achieving a harmonious balance between energy extraction, battery health, and longevity. To fulfill these stringent design criteria, an extensive investigation of parameter combinations, referred to as x and y parameters, has been carried out within the framework of the AEMS. The obtained data are compared with the results of the system controlled under constant DoD using only the battery, and the system is controlled adaptively with the same parameters using only the battery.

TABLE 5 Results of a simulation study

DoD	C-Rate	ESS	Time	Cycle	Energy (kWh)
$x=0.0125$	$y=0.0485$	Hybrid	6712.25	2652	1838.79
$x=0.0125$	$y=0.0485$	Battery-Only	6588.67	2437	1729.63
60	0.5	Battery-Only	6561.22	3084	1729.6
$x=0.0125$	$y=0.05$	Battery-Only	6550.55	2435	1724.9
70	0.5	Battery-Only	6135.57	2476	1612.74
80	0.5	Hybrid	6052.54	2401	1605.73
80	0.5	Battery-Only	5802.53	2050	1519.81
90	0.5	Battery-Only	5520.73	1734	1438.97
100	0.5	Battery-Only	5305.64	1484	1372.18

Table 5 shows that the optimum values for the weighting parameters x and y are 0.0125 and 0.0485, respectively, crucial in improving the battery's performance and ensuring it operates within predefined parameters for energy efficiency

and longevity. The proposed AEMS-controlled battery is initially used with 80% DoD, which is reduced to 60% over time as the battery ages. In addition, the charging current, which starts at 0.5C, is reduced to 0.375C as the battery ages. These adjustments are crucial to maintain the battery's long-term health and ensure a continuous high energy supply.

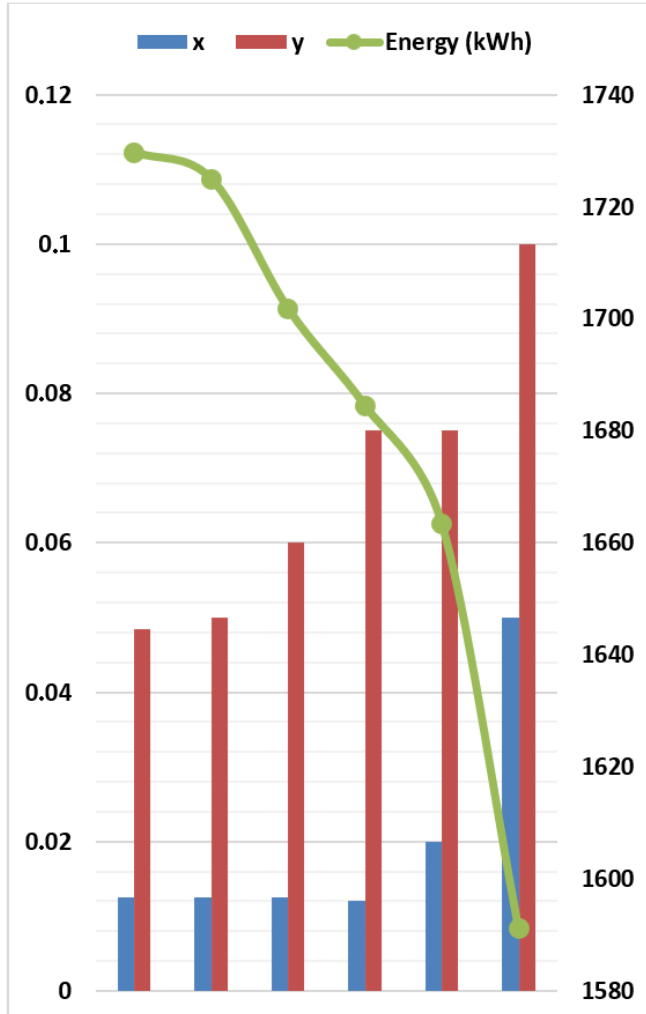


Fig. 7 Comparison of various weighting parameters in terms of energy

In fig. 8, the performance of the proposed AEMS is compared with systems generated and controlled under different conditions. First, comparing battery-only systems using fixed DoD and charging current settings are compared. The proposed AEMS exhibits a significant improvement of 13.81% in energy performance over the systems using fixed 80% DoD and 0.5C charging current. Moreover, it performs equal to the energy performance of the systems with a constant 60% DoD and 0.5C charging current. This result points to a significant advantage of AEMS. Although it allows deeper discharges and more energy utilization in each cycle, there is no loss in the overall benefit derived from the battery. This improves energy utilization efficiency and extends battery life. This makes AEMS a promising solution for optimizing battery usage in various applications. Secondly, a comparison with the hybrid system controlled by AEMS was performed. The energy obtained with the hybrid system

controlled by the same AEMS was observed to be 6.31% higher than the system using only batteries. These results show that the use of supercapacitors can delay battery aging. This analysis reveals that AEMS is a highly effective method of optimizing ESS operation. By dynamically updating DoD and charging current based on SoH, the design strikes a delicate balance between extracting more energy per cycle and preserving the battery's chemistry for longer. This balance results in improved energy performance, longer battery life, and enhanced overall system efficiency, making AEMS an essential tool for applications where consistent energy supply and long-term reliability are paramount.

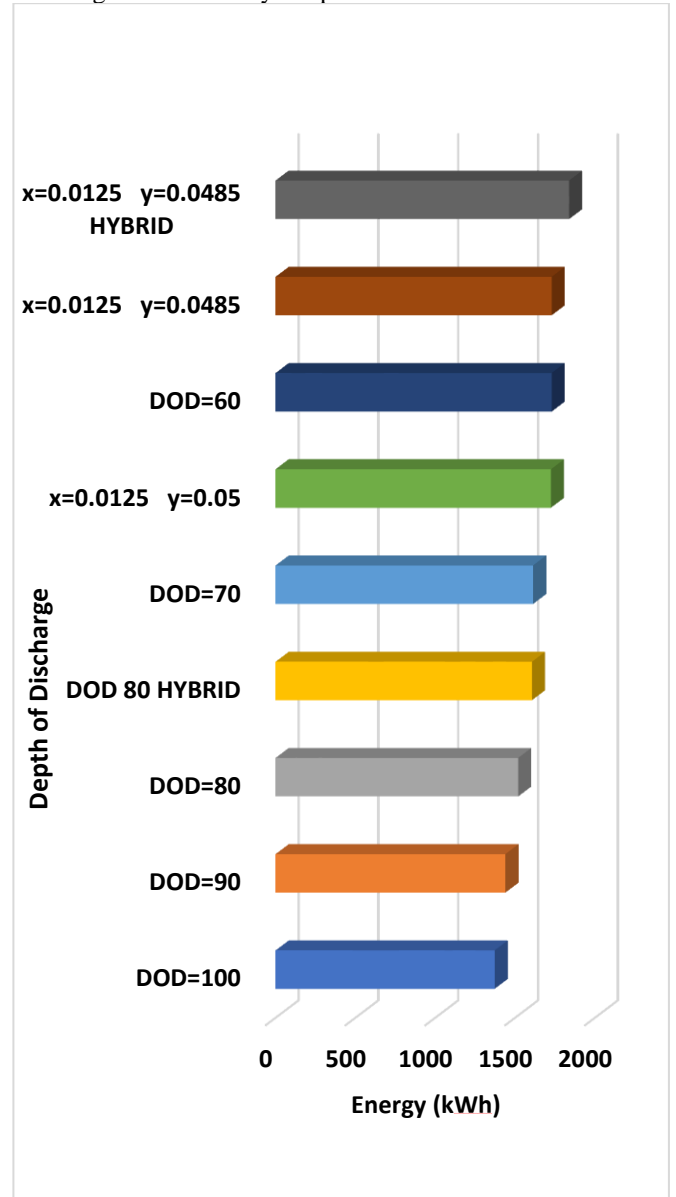


Fig. 8 Energy comparison of AEMS-controlled HESS with standard BEMS and AEMS-controlled battery-only systems

Figure 9 shows the current-sharing of the battery and supercapacitor that comprise the HESS during a cycle. Although the supercapacitor supports the battery for a short period, it prevents the battery from overloading and allows it to start supplying power more smoothly.

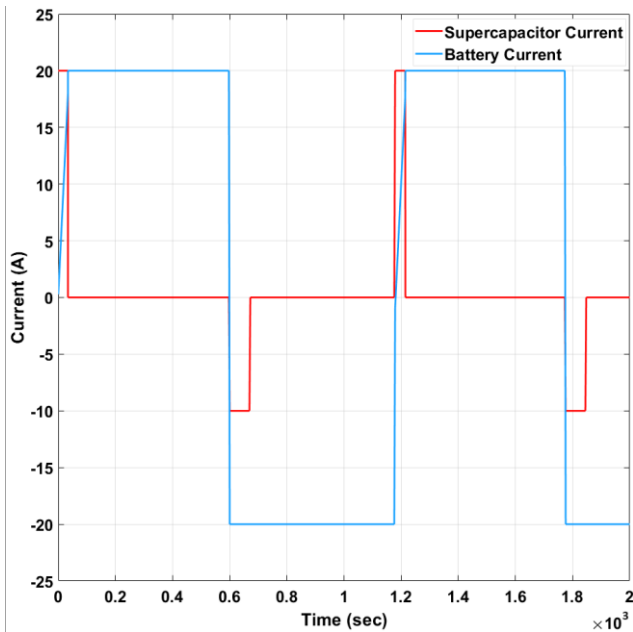


Fig. 9 Current sharing of battery and supercapacitor for a cycle

3.2. Battery Test Protocols

Many test protocols in the literature exist for testing batteries under realistic conditions. Test protocols are created by constantly renewing or changing parameters such as temperature, C-Rate, and standby time within a flow framework. Hybrid pulse power characterization (HPPC) and initial conditioning characterization test (ICCT) tests were applied to show the effects of the proposed study on battery life. The conditions of the HPPC protocol are given in fig. 10.

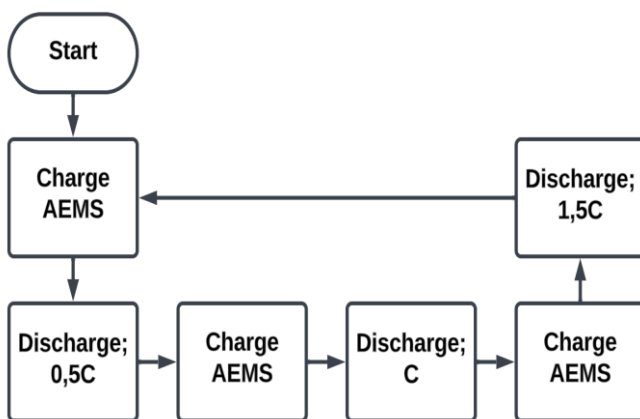


Fig. 10 HPPC Test Protocol

In the HPPC profile, the discharge current is increased in each discharge cycle [39]. Initially, 0.5C is used, 1C is used in the next cycle, and 1.5C is used in the last cycle. After every three cycles, it is returned to the beginning and repeated in this way for the entire battery life. Tests were performed for four different systems. Firstly, the battery-only system was tested under 0.5C constant C-Rate with 60% and 80% constant DoD parameters and standard energy management systems. Then, the battery-only and HESS systems using the adaptive energy management systems were tested separately.

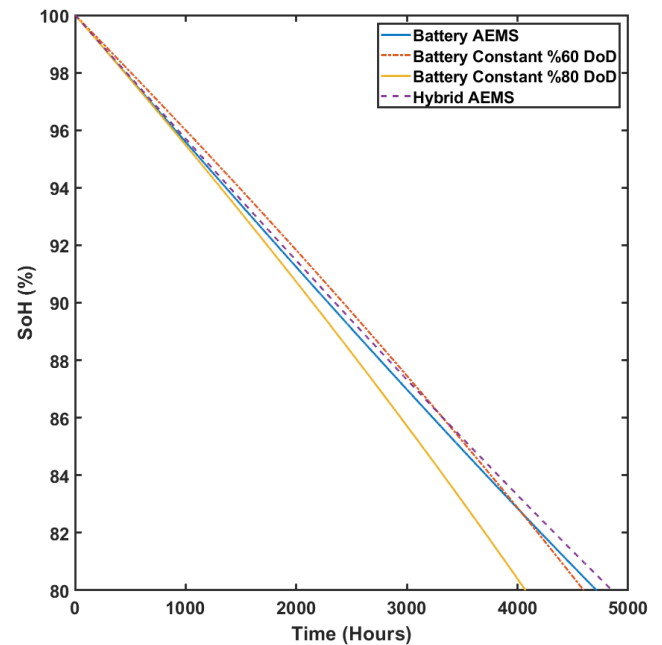


Fig. 11 SoH comparison of HPPC tests

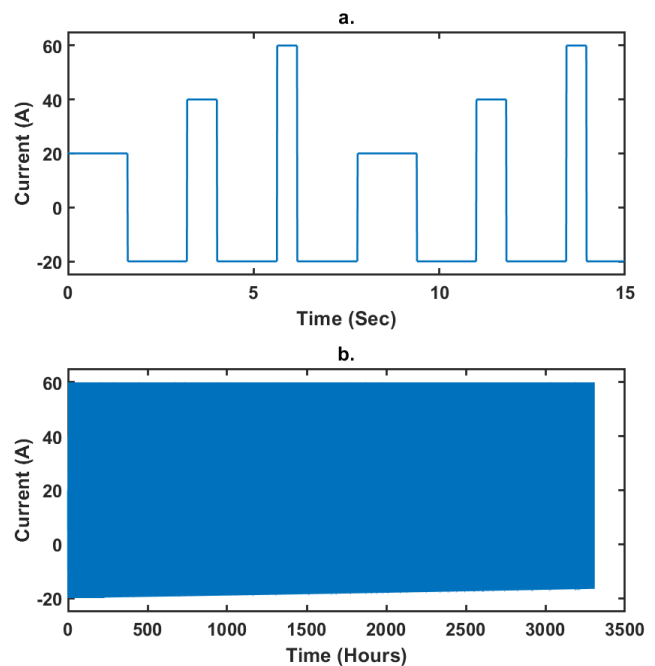


Fig. 12 a. HPPC Current Profile b. C-Rate effect on the HPPC test

The effect of HPPC test on SoH and comparison of tests in terms of SoH fig. 11. It is shown that the HESS controlled by AEMS offers longer battery life compared to the other systems. Figure 12.a illustrates the current profile of the HPPC test. The effect of the adaptive C-Rate parameter is clearly visible on fig. 12.b. As time passes and the battery ages, the charge current decreases. When the results were compared, 2334,614 kWh of energy was obtained in the system using HESS, and the superiority of the adaptive energy management system was demonstrated. HPPC test results are given in fig. 13.

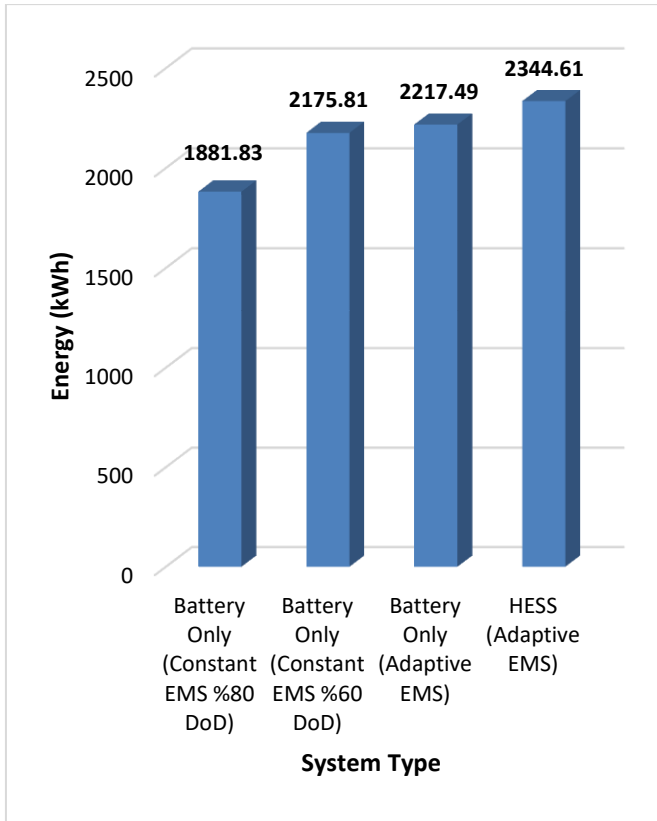


Fig. 13 HPPC Test Results

The second protocol used to test the system is ICCT. The ICCT test in fig. 14 tests the battery's compliance with the factory data [40], [41].

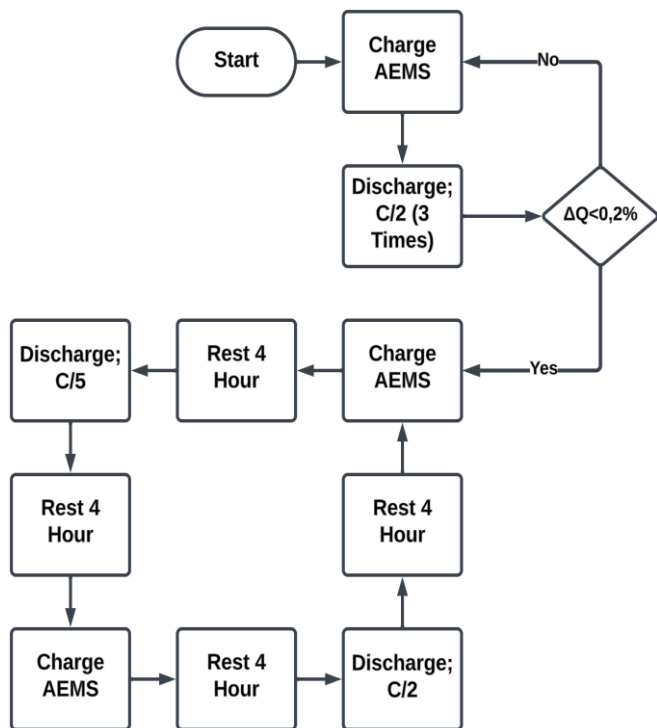


Fig. 14 ICCT Test Protocol

The protocol is designed to discharge continuously with 0.5C and 0.2C C-Rate parameters.

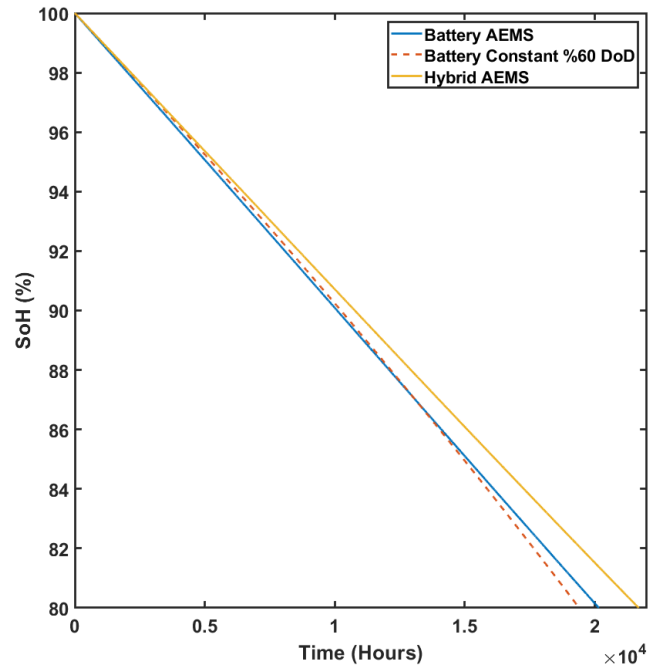


Fig. 15 SoH comparison of ICCT tests

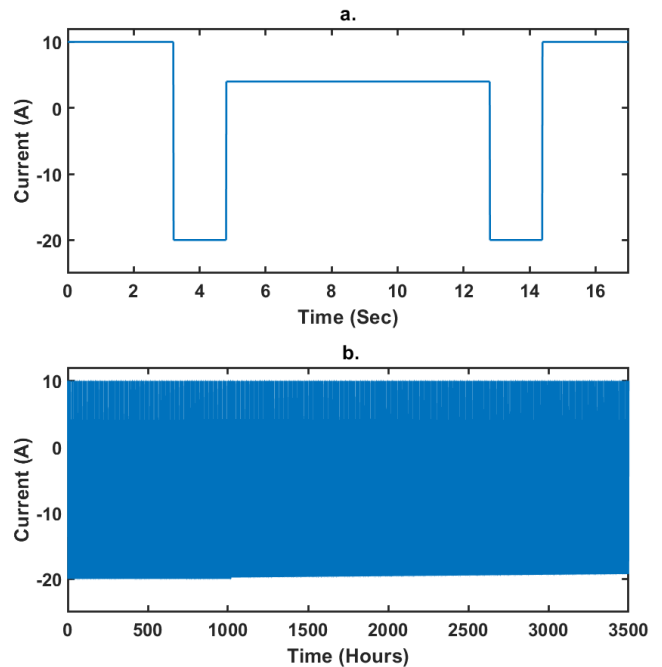


Fig. 16 a. Current Profile and b. C-Rate effect on the ICCT test

Firstly, the battery-only system was tested under 0.5C constant C-Rate with 80% constant DoD parameters and standard energy management systems. Then, the battery-only and HESS systems using the adaptive energy management systems were tested separately. Effect of ICCT test on SoH and comparing tests regarding SoH Figure 15. Compared to the other systems, the HESS controlled by AEMS has a longer battery life. Figure 16.a shows the actual ICCT test graphs. Additionally fig. 16.b. shows the effect of the adaptive C-rate parameter is clearly. The charge current decreases as time

passes and the battery ages. The data obtained from repeated tests until the battery life is exhausted are compared in fig. 17. When the results were compared, 1638,76 kWh of energy was obtained using HESS, bigger than the AEMS controlled battery system with %2,39 and standard EMS controlled battery only system with %3.09. The superiority of the adaptive energy management system was demonstrated with the ICCT test profile.

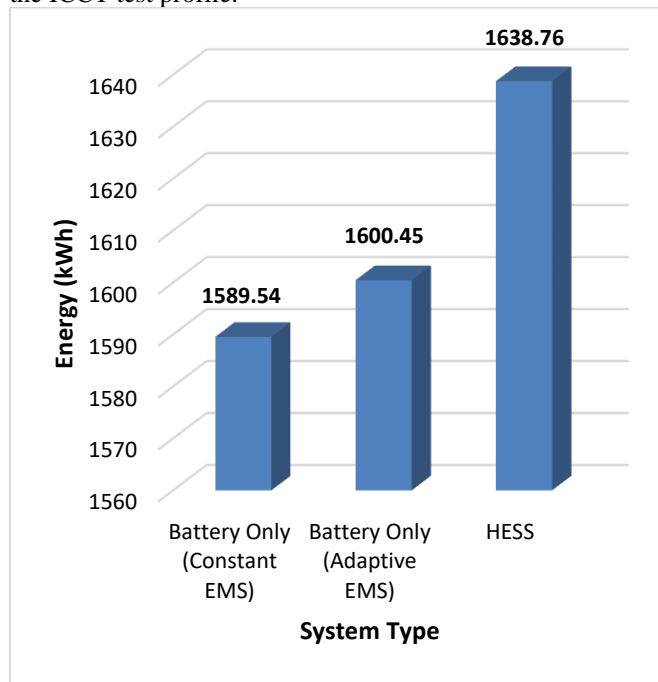


Fig. 17 ICCT Test Results

4. CONCLUSIONS

An adaptive energy management system (AEMS) for a battery-supercapacitor hybrid energy storage system (HESS) has been developed and simulated in this study. Dynamic Depth of Discharge (DoD) and C-Rate strategies extend the lifetime of lithium-based batteries and maximize energy utilization. However, a hybrid energy storage system is also created by integrating supercapacitors. Supercapacitors are known for their high power density and fast charge/discharge capabilities, which significantly increase the adaptability of the AEMS, reducing stress on the batteries and thus further extending battery life. Supercapacitors alleviate the load on the battery during sudden power demands and short-term power requirements, which increases energy efficiency and system resilience. This integration overcomes the limitations of battery-based systems, providing a faster and more efficient response capability to sudden load changes and high power demands.

The system allows the DoD and C-Rate parameters to vary according to the battery's State of Health (SoH) parameter, making it possible to operate the battery specifically for its current condition. In this way, AEMS maximizes the battery's operating life while ensuring efficient use of energy. AEMS not only ensures longer battery life and higher performance but also significantly reduces the cost of installation and maintenance by extending the battery replacement time.

Finally, the hybrid energy storage system created by supercapacitors integrated with the proposed Adaptive Energy Management System (AEMS) offers significant advantages regarding its environmental impact. The system contributes significantly to sustainability and reducing waste generation by reducing battery waste and replacement. This approach extends the lifetime of the batteries and prevents frequent battery replacement and waste, thus reducing the burden on the environment. The integration of supercapacitors can more efficiently meet peak energy demands, enabling battery systems to be used for more extended periods and generating less waste. This is an essential step towards reducing the environmental impact of energy storage solutions and demonstrates that AEMS promises a greener and more sustainable energy future. The effectiveness of using AEMS in hybrid storage systems has been proven by studies using fixed DoD and C-Rate settings and comparisons with battery-only systems controlled by AEMS. AEMS demonstrated a 13.81% improvement in energy performance compared to systems using a fixed 80% DoD and 0.5C charging current. Furthermore, AEMS performed on par with systems with a constant 60% DoD and 0.5C charging current, proving that despite allowing deeper discharges and higher energy utilization in each cycle, there was no loss in overall benefit. Furthermore, AEMS-controlled HESS achieved 6.31% higher energy utilization than battery-only systems. These findings suggest that being powered by supercapacitors can delay battery aging and improve overall system performance.

REFERENCES

- [1] K. Obaideen, A. G. Olabi, Y. Swailmeen, N. Shehata, M. Abdelkareem, A. Alami, C. Rodriguez, E. T. Sayed, "Solar Energy: Applications, Trends Analysis, Bibliometric Analysis and Research Contribution to Sustainable Development Goals (SDGs)," *Sustainability*, vol. 15, no. 2, pp. 1418-1453, 2023, doi: 10.3390/su15021418.
- [2] H. Feng, "The Impact of Renewable Energy on Carbon Neutrality for the Sustainable Environment: Role of Green Finance and Technology Innovations," *Front Environ Sci*, vol. 10, pp. 1-16, 2022, doi: 10.3389/fenvs.2022.924857.
- [3] X. H. Chen, K. Tee, M. Elnahass, and R. Ahmed, "Assessing the environmental impacts of renewable energy sources: A case study on air pollution and carbon emissions in China," *J Environ Manage*, vol. 345, pp. 118525-118537, 2023, doi: 10.1016/j.jenvman.2023.118525.
- [4] H. Dissanayake, N. Perera, S. Abeykoon, D. Samson, R. Jayathilaka, M. Jayasinghe, S. Yapa, "Nexus between carbon emissions, energy consumption, and economic growth: Evidence from global economies," *PLoS One*, vol. 18, no. 6, pp. 0287579, Jun. 2023, doi: 10.1371/journal.pone.0287579
- [5] E. Erdiwansyah, Mahidin, H. Husin, Nasaruddin, M. Zaki, and Muhibbuddin, "A critical review of the integration of renewable energy sources with various technologies," *Protection and Control of Modern Power Systems*, vol. 6, no. 1, pp. 3-20, 2021, doi: 10.1186/s41601-021-00181-3.
- [6] C. Wu, X.-P. Zhang, and M. Sterling, "Solar power generation intermittency and aggregation," *Sci Rep*, vol. 12, no. 1, p. 1-11, 2022, doi: 10.1038/s41598-022-05247-2.
- [7] K. Abaci, V. Yamaçlı, and Z. Chen, "Voltage stability improvement with coordinated ULTC-STATCOM controller and VSC-HVDC in high wind penetration cases," *Electrical Engineering*, vol. 103, no. 2, pp. 837-851, 2021, doi: 10.1007/s00202-020-01127-y.
- [8] N. Muzaffar, A. M. Afzal, H. H. Hegazy, and M. W. Iqbal, "Recent advances in two-dimensional metal-organic frameworks as an exotic candidate for the evaluation of redox-active sites in energy storage devices," *J Energy Storage*, vol. 64, pp. 107142, 2023, doi: 10.1016/j.est.2023.107142.
- [9] T. Costa, A. Arcanjo, A. Vasconcelos, W. Silva, C. Azevedo, A. Pereira, E. Jatoba, J.B. Filho, E. Barreto, M. G. Villalva, M. Marinho,

- “Development of a Method for Sizing a Hybrid Battery Energy Storage System for Application in AC Microgrid,” *Energies (Basel)*, vol. 16, no. 3, pp. 1175–1198 2023, doi: 10.3390/en16031175.
- [10] H. M. Amine, B. Aissa, H. Rezk, H. Mesaaoud, A. Othmane, M. Saad, M. A. Abdulkareem, “Enhancing hybrid energy storage systems with advanced low-pass filtration and frequency decoupling for optimal power allocation and reliability of cluster of DC-microgrids,” *Energy*, vol. 282, pp. 128310, 2023, doi: 10.1016/j.energy.2023.128310.
- [11] C. Pan, H. Fan, R. Zhang, J. Sun, Y. Wang, and Y. Sun, “An improved multi-timescale coordinated control strategy for an integrated energy system with a hybrid energy storage system,” *Appl Energy*, vol. 343, pp. 121137, 2023, doi: 10.1016/j.apenergy.2023.121137.
- [12] M. R. Çorapsız and H. Kahveci, “A study on Li-ion battery and supercapacitor design for hybrid energy storage systems,” *Energy Storage*, vol. 5, no. 1, pp. 386–394, 2023, doi: 10.1002/est2.386.
- [13] A. A. Abdalla, M. S. El Moursi, T. H. El-Fouly, and K. H. Al Hosani, “A Novel Adaptive Power Smoothing Approach for PV Power Plant with Hybrid Energy Storage System,” *IEEE Trans Sustain Energy*, vol. 14, no. 3, pp. 1457–1473, 2023, doi: 10.1109/TSTE.2023.3236634.
- [14] R. Powade and Y. Bhatshvar, “Design of semi-actively controlled battery-supercapacitor hybrid energy storage system,” *Mater Today Proc.*, vol. 72, pp. 1503–1509, 2023, doi: 10.1016/j.matpr.2022.09.378.
- [15] K. C. S. Lakshmi and B. Vedhanarayanan, “High-Performance Supercapacitors: A Comprehensive Review on Paradigm Shift of Conventional Energy Storage Devices,” *Batteries*, vol. 9, no. 4, pp. 902–946, 2023, doi: 10.3390/batteries9040202.
- [16] G. Yükses, Y. Muratoglu, and A. Alkaya, “Modelling of supercapacitor by using parameter estimation method for energy storage system,” *Advanced Engineering Science*, vol. 2, pp. 67–73, Mar. 2022.
- [17] M. Wiczorek, M. Lewandowski, and W. Jefimowski, “Cost comparison of different configurations of a hybrid energy storage system with battery-only and supercapacitor-only storage in an electric city bus,” *Bulletin of the Polish Academy of Sciences Technical Sciences*, vol. 67, no. No. 6, pp. 1095–1106, 2019, doi: 10.24425/bpasts.2019.131567.
- [18] C. Kök and A. Alkaya, “Investigation of Thermal Behavior of Lithium-Ion Batteries under Different Loads,” *European Mechanical Science*, vol. 4, no. 3, pp. 96–102, 2020, doi: 10.26701/ems.635707.
- [19] B. Tepe, S. Jablonski, H. Hesse, and A. Jossen, “Lithium-ion battery utilization in various modes of e-transportation,” *eTransportation*, vol. 18, pp. 100274, 2023, doi: 10.1016/j.etrans.2023.100274.
- [20] X. Li, M. Li, M. Habibi, N. Najaafi, and H. Safarpour, “Optimization of hybrid energy management system based on high-energy solid-state lithium batteries and reversible fuel cells,” *Energy*, vol. 283, pp. 128454, 2023, doi: 10.1016/j.energy.2023.128454.
- [21] G. Yükses and A. Alkaya, “A novel state of health estimation approach based on polynomial model for lithium-ion batteries,” *Int J Electrochem Sci*, vol. 18, no. 5, pp. 100111, 2023, doi: 10.1016/j.ijoes.2023.100111.
- [22] M. Hossain, M. E. Haque, and M. T. Arif, “Online Model Parameter and State of Charge Estimation of Li-Ion Battery Using Unscented Kalman Filter Considering Effects of Temperatures and C-Rates,” *IEEE Transactions on Energy Conversion*, vol. 37, no. 4, pp. 2498–2511, 2022, doi: 10.1109/TEC.2022.3178600.
- [23] A. T. Elsayed, C. R. Lashway, and O. A. Mohammed, “Advanced Battery Management and Diagnostic System for Smart Grid Infrastructure,” *IEEE Trans Smart Grid*, vol. 7, no. 2, pp. 897–905, 2016, doi: 10.1109/TSG.2015.2418677.
- [24] G. Yükses and A. Alkaya, “Effect of the Depth of Discharge and C-Rate on Battery Degradation and Cycle Life,” in *2023 14th International Conference on Electrical and Electronics Engineering (ELECO)*, 2023, doi: 10.1109/ELECO60389.2023.10415967.
- [25] M. Robayo, M. Mueller, S. Sharkh, and M. Abusara, “Assessment of supercapacitor performance in a hybrid energy storage system with an EMS based on the discrete wavelet transform,” *J Energy Storage*, vol. 57, pp. 106200, 2023, doi: 10.1016/j.est.2022.106200.
- [26] S. K. Kollimalla, A. Ukil, H. B. Gooi, U. Manandhar, and N. R. Tummuru, “Optimization of Charge/Discharge Rates of a Battery Using a Two-Stage Rate-Limit Control,” *IEEE Trans Sustain Energy*, vol. 8, no. 2, pp. 516–529, 2017, doi: 10.1109/TSTE.2016.2608968.
- [27] Y. Basheer, S. M. Qaisar, A. Waqar, F. Lateef, and A. Alzahrani, “Investigating the Optimal DOD and Battery Technology for Hybrid Energy Generation Models in Cement Industry Using HOMER Pro,” *IEEE Access*, vol. 11, pp. 81331–81347, 2023, doi: 10.1109/ACCESS.2023.3300228.
- [28] A. Bavand, S. A. Khajehoddin, M. Ardakani, and A. Tabesh, “Online Estimations of Li-Ion Battery SOC and SOH Applicable to Partial Charge/Discharge,” *IEEE Transactions on Transportation Electrification*, vol. 8, no. 3, pp. 3673–3685, 2022, doi: 10.1109/TTE.2022.3162164.
- [29] L. Timilsina, P. R. Badr, P. H. Hoang, G. Ozkan, B. Papari, and C. S. Edrington, “Battery Degradation in Electric and Hybrid Electric Vehicles: A Survey Study,” *IEEE Access*, vol. 11, pp. 42431–42462, 2023, doi: 10.1109/ACCESS.2023.3271287.
- [30] M. S. Wasim, S. Habib, M. Amjad, A. R. Bhatti, E. M. Ahmed, and M. A. Qureshi, “Battery-Ultracapacitor Hybrid Energy Storage System to Increase Battery Life Under Pulse Loads,” *IEEE Access*, vol. 10, pp. 62173–62182, 2022, doi: 10.1109/ACCESS.2022.3182468.
- [31] S. Xie, S. Qi, and K. Lang, “A Data-Driven Power Management Strategy for Plug-In Hybrid Electric Vehicles Including Optimal Battery Depth of Discharging,” *IEEE Trans Industr Inform*, vol. 16, no. 5, pp. 3387–3396, 2020, doi: 10.1109/TII.2019.2917468.
- [32] Z. Zhang, K. Wen, and W. Sun, “Optimization and sustainability analysis of a hybrid diesel-solar-battery energy storage structure for zero energy buildings at various reliability conditions,” *Sustainable Energy Technologies and Assessments*, vol. 55, pp. 102913, 2023, doi: 10.1016/j.seta.2022.102913.
- [33] O. Ibrahim, M. S. Bakare, T. I. Amosa, A. O. Otuoze, W. O. Owonikoko, E. M. Ali, L. M. Adesina, O. Ogunbiyi, “Development of fuzzy logic-based demand-side energy management system for hybrid energy sources,” *Energy Conversion and Management: X*, vol. 18, pp. 100354, 2023, doi: 10.1016/j.ecmx.2023.100354.
- [34] T. H. B. Huy, H. T. Dinh, and D. Kim, “Multi-objective framework for a home energy management system with the integration of solar energy and an electric vehicle using an augmented ϵ -constraint method and lexicographic optimization,” *Sustain Cities Soc*, vol. 88, pp. 104289, 2023, doi: 10.1016/j.scs.2022.104289.
- [35] S.-J. Park, Y. W. Song, B. S. Kang, W. J. Kim, Y. J. Choi, C. Kim, Y.S. Hong, “Depth of discharge characteristics and control strategy to optimize electric vehicle battery life,” *J Energy Storage*, vol. 59, pp. 106477, 2023, doi: 10.1016/j.est.2022.106477.
- [36] M. I. Hlal, V. K. Ramachandaramurthy, A. Sarhan, A. Pouryekt, and U. Subramaniam, “Optimum battery depth of discharge for off-grid solar PV/battery system,” *J Energy Storage*, vol. 26, pp. 100999, 2019, doi: 10.1016/j.est.2019.100999.
- [37] L. Setyawan, J. Xiao, and P. Wang, “Optimal Depth-of-Discharge range and capacity settings for battery energy storage in microgrid operation,” in *2017 Asian Conference on Energy, Power and Transportation Electrification (ACEPT)*, 2017, pp. 1–7. doi: 10.1109/ACEPT.2017.8168560.
- [38] S. N. Motapon, E. Lachance, L.-A. Dessaint, and K. Al-Haddad, “A Generic Cycle Life Model for Lithium-Ion Batteries Based on Fatigue Theory and Equivalent Cycle Counting,” *IEEE Open Journal of the Industrial Electronics Society*, vol. 1, pp. 207–217, 2020, doi: 10.1109/OJIES.2020.3015396.
- [39] T. Białoń, R. Niestrój, W. Skarka, and W. Korski, “HPPC Test Methodology Using LFP Battery Cell Identification Tests as an Example,” *Energies (Basel)*, vol. 16, no. 17, pp. 6239–6259, 2023, doi: 10.3390/en16176239.
- [40] M. Dubarry and A. Devie, “Battery durability and reliability under electric utility grid operations: Representative usage aging and calendar aging,” *J Energy Storage*, vol. 18, pp. 185–195, 2018, doi: 10.1016/j.est.2018.04.004.
- [41] A. Devie, G. Baure, and M. Dubarry, “Intrinsic Variability in the Degradation of a Batch of Commercial 18650 Lithium-Ion Cells,” *Energies (Basel)*, vol. 11, no. 5, pp. 1031–1044, 2018, doi: 10.3390/en11051031.