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Optimizing the lifespan of lithium-ion batteries for piezoelectric devices using dynamic controllers and AI models

Abstract: Powering small biomedical and Internet-of-Things devices with piezoelectric harvesters is challenging because the available power is low, intermittent, and difficult to condition, which can actually overstress storage elements if charging is not adapted. This study evaluates lithium-ion battery longevity under such constraints using NASA PCoE datasets and designs charge policies matched to limited source power. Firstly, we examine temperature – voltage behavior, and identify a moderate operating window, which motivates a slow-charge baseline that reduces electrochemical stress. Secondly, we introduce two control layers: a dynamic, rule-based controller that derates current as terminal voltage approaches 4.2 V or temperature exceeds 24°C within a defined safe window, and intelligent controllers (Random Forest, XGBoost, Gradient Boosting) that predict incremental degradation from routinely measured signals and select the current that minimizes expected damage under the same constraints. Using the number of cycles to SoH = 0.7 as the endpoint, dynamic control extends life from 30 to 43 cycles, while the intelligent controllers reach 45, 47, and 48 cycles. Reduced voltage peaks and ripple, together with lower thermal exposure, support the mechanism. Overall, aligning slow, condition-aware, and predictive charging with

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piezoelectric availability robustly extends service life and improves energy-capture efficiency, enabling more reliable, lower-maintenance biomedical and Internet-of-Things systems.

Keywords: optimizing the lifespan of lithium-ion batteries, piezoelectric devices, machine learning, powering biomedical devices, controllers

Introduction

Optimizing battery life remains a significant and persistent challenge across renewable energy systems, mobile electronics, and embedded power technologies. Particularly for piezoelectric batteries, which are crucial for powering small biomedical devices. Effective energy management is one of the most pressing issues faced by biomedical sensors, especially in wearable and implantable applications.

The limited lifespan of batteries presents a significant challenge to the continuous operation of these devices. Ensuring uninterrupted, long-term sensor performance requires a stable and efficient power supply to minimize the frequency of recharging. This is especially critical in biomedical applications, where consistent and reliable monitoring is vital to addressing patient needs and maintaining high standards of care (Raza et al. 2024). Numerous research initiatives have been undertaken in this field, introducing innovative solutions to extend battery lifespan. These efforts have focused on optimizing data processing algorithms and leveraging advanced technologies, including energy storage systems and wireless charging methods (Ray et al. 2020). The field of health monitoring through the Internet of Medical Things (IoMT) faces several challenges, including high device power consumption, frequent topology changes, sensor interference, and the absence of standardized routing protocols. To address these issues, various innovative strategies have been proposed in the literature. One approach involves energy-efficient routing protocols based on clustering algorithms, which minimize unnecessary transmissions and enhance network efficiency. Another solution focuses on intelligent channel access management, employing optimized MAC protocols to maintain high-quality service while reducing energy consumption. Advanced mobility models have been developed to analyze and predict user behavior, facilitating more efficient resource allocation and enhancing overall system performance (Wei et al. 2020).

Lithium-ion batteries are widely recognized for their high energy density, long lifespan, and low self-discharge rates. However, they inevitably experience capacity loss and a decline in their state of health (SoH) over time. Factors such as the number of charge/discharge cycles, temperature, and current load significantly contribute to this degradation (Yang et al. 2020). Temperature critically affects Li-ion cell behavior by altering internal resistance and accelerating degradation mechanisms. Moderate temperature increases can reduce internal resistance primarily through enhanced ionic conductivity and lower charge-transfer impedance, improving short-term performance. However, sustained high temperatures accelerate parasitic reactions and raise self-discharge, which reduces the available capacity within a given cycle and contributes indirectly to faster long-term aging. We therefore treat temperature as a key constraint in our control design (Barcellona et al. 2022; Werner et al. 2021).

Research indicates that optimizing charging techniques, such as deferred charging, can enhance battery performance and extend lifespan by mitigating internal degradation. These strategies take into account internal electrochemical processes and operating conditions (Woody et al. 2020). For instance, lower charging currents alleviate stress on internal materials, minimizing detrimental effects like lithium plating and particle cracking, thereby prolonging battery life.

Piezoelectric devices offer a new way to recharge batteries in this context. They present an interesting option for cases where traditional energy sources are limited, since they can convert mechanical vibrations into electrical energy (Qian et al. 2019). However, piezoelectric power generation tends to be rather modest and pulsed (Sirigireddy and Eladi 2023), which creates specific challenges when it comes to storing energy. An appropriate approach is needed, one that maximizes battery charging efficiency while minimizing stress on the battery. The main objective is to optimize the lifespan of lithium-ion batteries charged by piezoelectric devices. The particular characteristics of piezoelectric, notably their low current and variable voltage, lend themselves naturally to slow charging. This approach is particularly advantageous for several reasons. Compatibility with the power generated, piezoelectric produces low, pulsed power, perfectly matching slow charging conditions, which limit charging current and reduce stress on the battery. The paper (Goodenough and Kim 2011) discusses how slow charging can limit charging current and reduce stress on the battery by minimizing the risk of dendrite formation and maintaining acceptable polarization. Reducing stress on the battery, slow charging minimizes thermal and mechanical stress, thus delaying degradation phenomena such as excessive SEI (Solid Electrolyte Interface) film formation and harmful secondary reactions (Zong et al. 2020). Stability of voltage curves, by promoting stable charging, the voltage remains uniform, thus avoiding the harmful fluctuations seen in rapid charging methods. To test this hypothesis, data from NASA's lithium-ion battery dataset were utilized ("CapstoneProject/Analysis_B0005.ipynb at master · Kalrfou/CapstoneProject" n.d.). By analyzing charge and discharge cycles, the impact of slow charging on battery life and state of health (SoH) was assessed. Piezoelectric devices have a weak point; despite their ability to create high voltages, the current they produce is still modest, which makes energy storage challenging (Di Li et al. 2022). The electronic circuits designed to capture this energy need to take this property into account. One way to address the issue is by adding a capacitor or supercapacitor upstream of the battery. This component is key to ensuring a more consistent charge transfer tailored to the battery's needs, helping stabilize voltage fluctuations and temporarily store the energy generated by the piezoelectric device. In this way, the input current meets the battery's charging standards, which not only improves storage efficiency but also reduces the risk of damage to the battery.

This study looks at the data of lithium-ion batteries through a multi-stage approach ("CapstoneProject/Analysis_B0005.ipynb at master · Kalrfou/CapstoneProject" n.d.). It involves

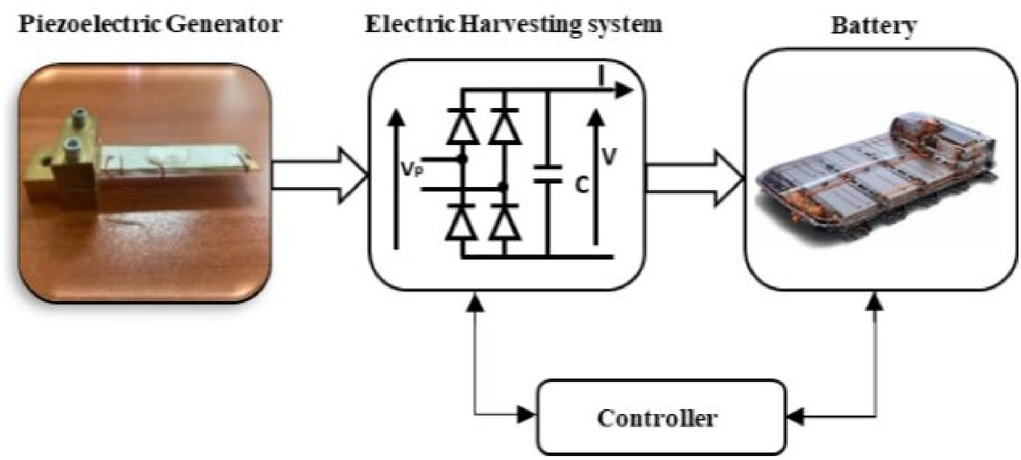

Fig. 1. Global system diagram

Rys. 1. Globalny schemat systemu

applying a slow charge to match the characteristics of the piezoelectric device and measuring its impact on the battery's SoH. This approach helps extend the battery's lifespan and prevent excessive electrochemical stress. To provide stable voltage and the right current, dynamic optimization was followed by real-time adjustments to the charging parameters using a dynamic controller. As a result, overall efficiency improved, and energy losses were reduced. AI-based models (Khawaja et al. 2023; How et al. 2020) were then used to predict the electrochemical behavior of the battery and adjust charging settings (Lipu et al. 2018; Raoofi and Yıldız 2023), aiming to enhance charge management even further. It has been shown that these models significantly reduce deterioration and help optimize the battery's lifespan (Chen et al. 2021). The goal of this research is to extend the lifespan of lithium-ion batteries by combining cutting-edge charge management strategies with the unique properties of piezoelectric devices. By using adaptive control mechanisms and delayed charging, innovative and sustainable energy storage systems are made possible.

This paper is structured to gradually cover the different stages of battery lifespan optimization, focusing particularly on piezoelectric batteries. First, the state of health (SoH) of the battery is introduced as a key metric for assessing its performance and degradation over time. Next, the effect of temperature on battery voltage is examined to show how it impacts lithium-ion battery performance. The following section looks at slow charging, which has been shown to be an effective method for prolonging battery life. To adjust the charging current proactively, a Dynamic Controller is introduced. Its impact is explained in two subsections: the Impact of the Dynamic Controller on Charging Current, which explores dynamic adjustments, and the Impact of Dynamic Charging on SoH, which demonstrates how this method helps improve SoH. The optimization of piezoelectric battery lifespan is then explored in detail, focusing on the modest energy flows produced by these devices. The Intelligent Controllers section presents methods based on artificial intelligence models to push this even further. Three models are discussed: Random Forest, Gradient Boosting, and XGBoost, all promising for improving battery life and extending charge cycles. The Battery Life Optimization section wraps up by summarizing the results and performance improvements enabled by the proposed strategies. The paper concludes with a summary of the progress made and future prospects for intelligent and sustainable energy systems tailored to piezoelectric devices.

1. State of Health (SoH)

A battery's State of Health (SoH) is a metric that compares its present operational capability to its original or nominal state (Lin et al. 2025). SoH, which is often given as a percentage, shows how much energy the battery can still store and distribute effectively. In key applications like electric cars, renewable energy systems, and on-board electronics, monitoring is crucial for determining the battery's remaining life, preventing early failure, and optimizing charge/discharge cycles to maintain dependable operation.

Equation 1 states that battery SOH is calculated as capacity fading with regard to the first cycle, where is the capacity at the first cycle as established by a complete charge-discharge procedure and is the capacity value at the *i*-th cycle (Roman et al. 2021).

$$SoH = \frac{C_i}{C_0} \tag{1}$$

The procedures used to estimate and optimize the state of health (SoH) of batteries are primarily broken down into three stages, as seen in Figure 1.

In order to get vital raw data that will form the foundation of analysis, such as voltage, current, and temperature, the initial stage is performing battery aging tests. Using techniques to estimate and optimize the SoH throughout the charge and discharge cycles is the second phase. A dynamic controller that modifies the parameters in real-time and three controllers based on artificial intelligence (AI) models, Random Forest, XGBoost, and Gradient Boosting, have been built in this study. These controller types will be covered in more detail in the sections that follow. The last phase is to assess each controller's influence on the SoH. The ability of various controllers to optimize the SoH over the course of the battery's life cycles is compared.

These phases demonstrate the efficacy of each technique while offering a clear framework for the examination and confirmation of the suggested strategies.

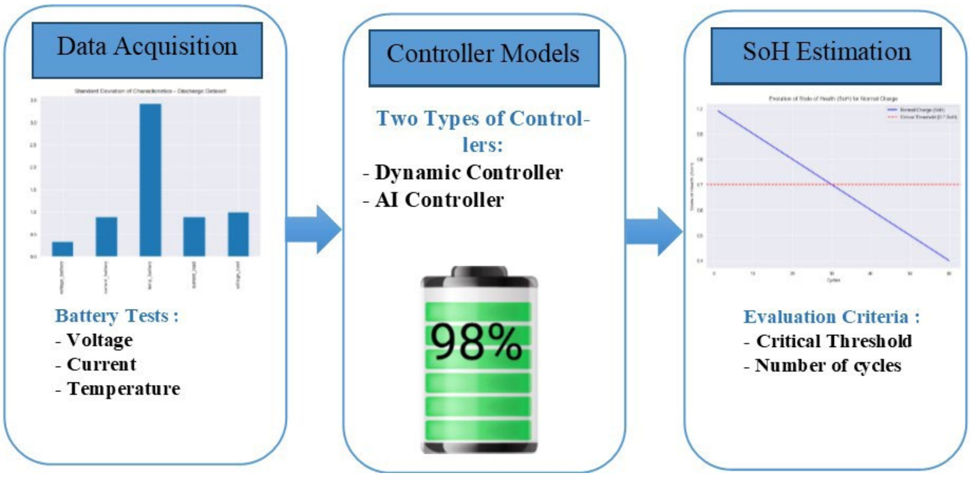

Fig. 2. State of Health (SoH)

Rys. 2. Wskaźnik kondycji baterii (SoH)

2. Impact of temperature on battery voltage

Temperature strongly influences terminal voltage and, by extension, energy efficiency. Battery operation is best within a moderate temperature window; outside this window, whether too cold or too hot, changes in internal resistance and reaction kinetics degrade performance and can accelerate aging.

Figure 3 highlights a non-linear relationship between temperature and terminal voltage. Within a moderate temperature window, lower internal resistance helps keep the voltage relatively stable. At low temperatures, higher internal resistance leads to lower voltage and slower dynamics. At elevated temperatures, the voltage may appear acceptable in the short term, but parasitic reactions accelerate, increasing electrochemical stress and speeding up aging. In line with Figure 3, when $T > 24$ °C or V approaches 4.2 V, the charging current is stepped down until the cell re-enters the safe window. Conversely, once T and V are back within nominal limits for a short hysteresis period, the current is increased gradually with the same step size, without exceeding the allowed setpoint. These observations motivate our thermal derating strategy; the charging current is reduced as soon as the cell drifts outside the safe window, which protects health and extends service life.

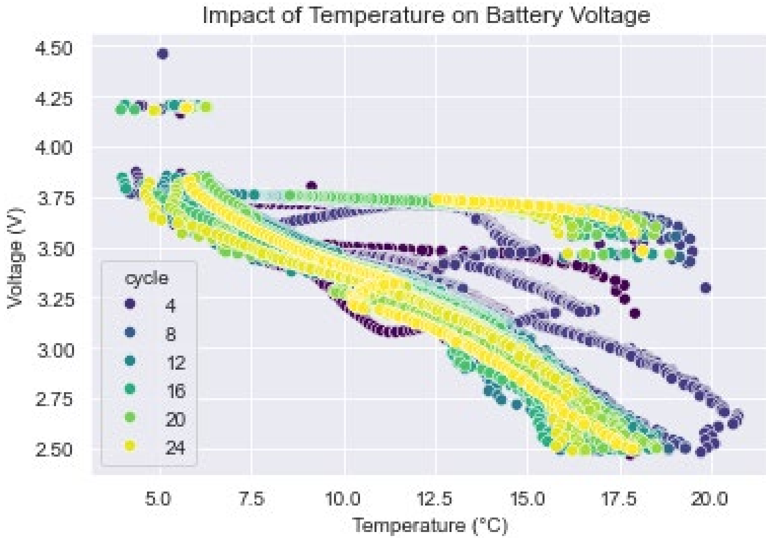

Fig. 3. Impact of temperature on battery voltage

Rys. 3. Wpływ temperatury na napięcie baterii

3. Methods

3.1. Slow charging

Slow charging is especially useful during the initial phase of charging to minimize stress on battery components, and for end-of-life cells with higher internal resistance, where it reduces the risk of further degradation. It is also preferred in devices where long-term autonomy matters more than speed, such as medical devices or renewable-energy storage systems.

In our study, slow charging is implemented as an ≈20% reduction in current with a feedback loop that keeps the terminal voltage within a low-stress window. The goal is to limit voltage peaks/ripple and thus electrochemical stress, consistent with the idea that slow charging fatigues the cell less over time.

Figure 4 compares normal and slow-charge voltage profiles. Although the curves largely overlap, as expected because both strategies enforce the same voltage ceiling, the slow-charge profile shows lower peak excursions and ripple and a gentler rise/stabilization, classic indicators of reduced electrochemical stress. This aligns the policy with the low, intermittent power available from piezoelectric harvesters and helps delay SoH degradation, extending service life in biomedical and IoT applications. Reduced peaks and ripple under slow charge also motivate the controller choices used in the paper.

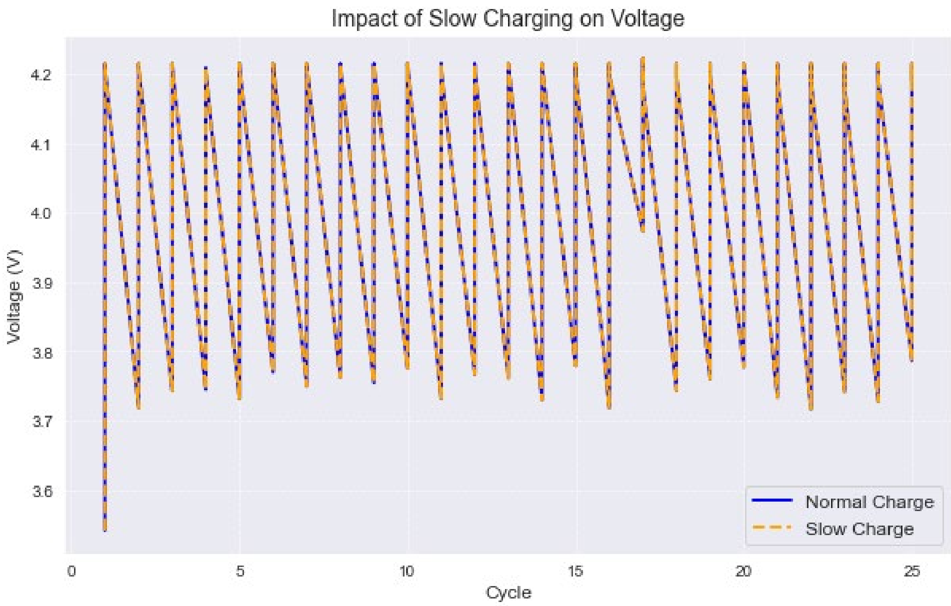

Fig. 4. Impact of slow charging on voltage

Rys. 4. Wpływ powolnego ładowania na napięcie

3.2. Dynamic controller

To complement slow charging, we integrate a dynamic charge controller (Fig. 5) that adapts the charging current in real time to minimize electrochemical stress and extend battery life – particularly important for piezoelectric sources with low, intermittent power. Based on Figure 3, our strategy applies thermal derating: when T > 24 °C or V approaches 4.2 V, the charging current is stepped down to bring the cell back into the safe window; conversely, it is increased gradually once T and V return to nominal levels. The controller also considers SoH, applying gentler currents to aged, higher-impedance cells. By preventing voltage/temperature peaks and limiting conditions that trigger parasitic reactions, the controller reduces degradation, curbs rapid capacity loss at elevated temperatures, and improves thermal management. By keeping peaks and ripple lower, limiting time near high voltage, and avoiding elevated temperatures, the controller reduces parasitic reactions and heat-driven degradation pathways. In our study, this policy, combined with slow charging delays SoH deterioration, extending the number of useful cycles before the SoH = 0.7 threshold is reached. In short, the controller turns the qualitative insights of Fig. 3 into quantitative, step-wise current decisions that both respect safety and fit the realities of a piezoelectric power budget.

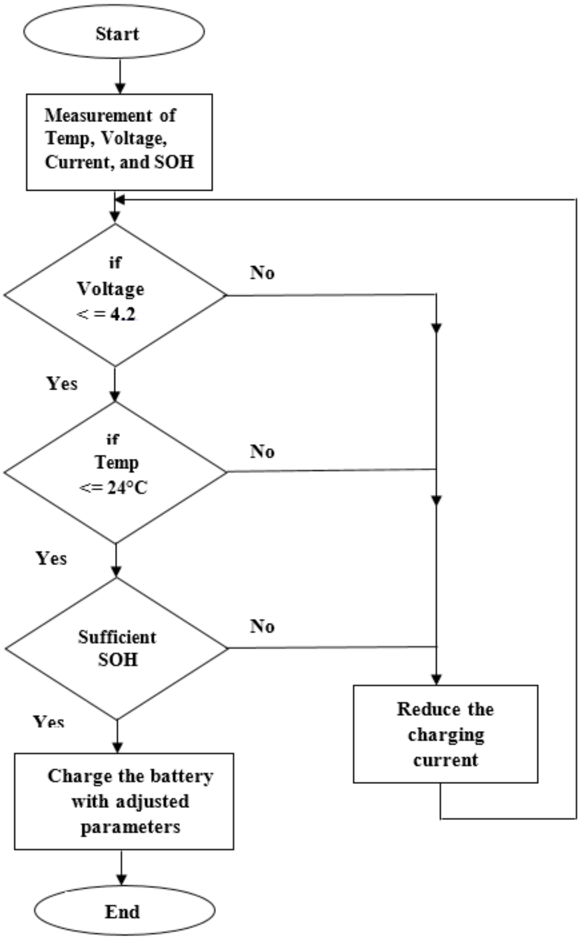

Fig. 5. Flowchart of the dynamic controller

Rys. 5. Schemat blokowy kontrolera dynamicznego

3.3. Intelligent controllers

Intelligent Controllers, beyond our rule-based dynamic approach, we explore AI-assisted controllers, Random Forest, XGBoost, and Gradient Boosting, to refine current selection during slow charging of piezo-powered batteries. These models use routinely measured signals (V, I, T, cycle index, prior SoH) to anticipate stress and propose safe setpoints under voltage/temperature constraints. Below, we describe the models, features, and safety logic, and their effect on SoH and cycles-to-threshold is evaluated later in the Results.

3.3.1. Random forest

The Random Forest model is an ensemble learning technique that builds many decision trees using randomly selected subsets of data and characteristics, rather than a single tree that may be prone to overfitting. The final output is obtained either by majority voting (for classification tasks) or by averaging the results, which greatly reduces the likelihood of overlearning errors and improves the model's ability to generalize to unknown inputs.

One of Random Forest's key benefits is its ability to tolerate noise and data fluctuations, which makes it perfect for complex applications like battery management. The model may look at a number of factors related to battery behavior and performance, including the State of Health (SoH), battery temperature, and previous charge cycles. Random Forest is a helpful tool for developing intelligent and adaptable battery management systems since it can dynamically enhance the charging process in real-world battery management applications by predicting when to reduce the charging current in order to prevent overcharging or thermal stress.

3.3.2. XGBoost (Extreme Gradient Boosting)

The powerful supervised learning model XGBoost is based on the boosting technique. It works by regularly combining a number of weak learners, typically decision trees, to create a strong and accurate prediction model. Each decision tree corrects the errors of its predecessors to produce a model that excels at handling both linear and non-linear interactions. One of the key benefits of XGBoost is its ability to manage complex interdependencies among several input variables, such as battery temperature, voltage, current, and the State of Health (SoH). By successfully capturing these intricate linkages, it generates precise predictions even when dealing with noisy or high-dimensional data. Furthermore, XGBoost can handle large datasets well and deliver forecasts in real time thanks to its excellent computational efficiency design. In the context of battery management, XGBoost is able to predict charging requirements based on the battery's current status, which includes its temperature, voltage, and overall health. These predictions enable dynamic adjustments to the charging current, hence optimizing the charging process. By preventing overcharging or excessive heat production, this flexibility improves energy efficiency and extends the battery's lifespan. Therefore, XGBoost is a crucial tool for developing intelligent battery management systems that balance performance, safety, and lifespan.

3.3.3. Gradient boosting

Gradient boosting is a machine learning technique that builds prediction models iteratively, improving accuracy with each iteration. Unlike traditional decision tree methods, it emphasizes mistake reduction by creating new trees that focus on the errors made by earlier ones. This process continues until the model achieves the desired level of accuracy or error reduction. Because it can spot minute correlations in data, gradient boosting is incredibly helpful in dynamic battery management systems. For instance, it could account for minor changes in variables like temperature, voltage, or the battery's internal resistance that are typically disregarded. By mimicking these subtle patterns, it can produce projections of charging needs that are remarkably accurate. Gradient Boosting may modify the charging current to optimize battery performance and lifetime due to its precision. Gradient boosting is a useful technique for complex system management, like batteries, where precision and adaptability are crucial, due to its ability to handle such intricate dynamics.

Thus, an intelligent charge management system that can address the unique requirements of batteries driven by sporadic energy sources like piezoelectric generators may be developed thanks to these three AI models. These models assist in maximizing battery life while guaranteeing steady, effective charging because of their capacity to handle intricate data and adjust to dynamic changes.

4. Results

We present here the impact of different charging strategies on battery health (SoH), the standard baseline, dynamic control, and the three AI-based controllers (Random Forest, XGBoost, and Gradient Boosting). The evaluation draws notably on the number of cycles required to reach SoH = 0.7, as well as on the analysis of voltage and temperature profiles (peaks, ripple). We report and compare the gains achieved, linking the observations to electrochemical stress mechanisms, the parameters and models are described in the Methods section, and the numerical comparisons are shown in Figures 6–8.

4.1. Impact of the dynamic controller on the charging current

Figure 6's blue Normal Charge curve demonstrates that, despite changes in the battery's voltage, temperature, or state of health (SoH), the charging current stays constant throughout the cycles. On the other hand, the dynamic charge orange curve shows a gradual adaptation of current to battery conditions, with current being proactively decreased as soon as temperature or voltage reaches critical limits. In this way, current peaks are significantly attenuated, especially from advanced cycles onwards, minimizing stress on the battery and optimizing its lifespan.

The gradual reduction of current in the dynamic curve reduces stress on the battery's internal components, avoiding extreme conditions of overcharging or overheating. Indeed, a constant charging current, as in the case of normal charging, can lead to excessive temperature rise or overcharging of the battery, accelerating chemical degradation of the cells. This dynamic

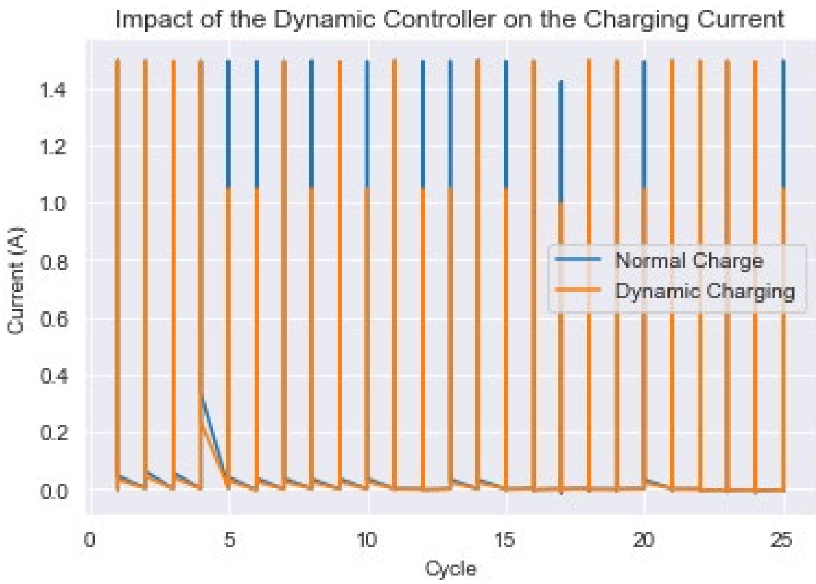

Fig. 6. Impact of the dynamic controller on the charging current

Rys. 6. Wpływ regulatora dynamicznego na prąd ładowania

Fig. 7. Impact of dynamic charge on SoH

Rys. 7. Wpływ dynamicznego ładowania na SoH baterii

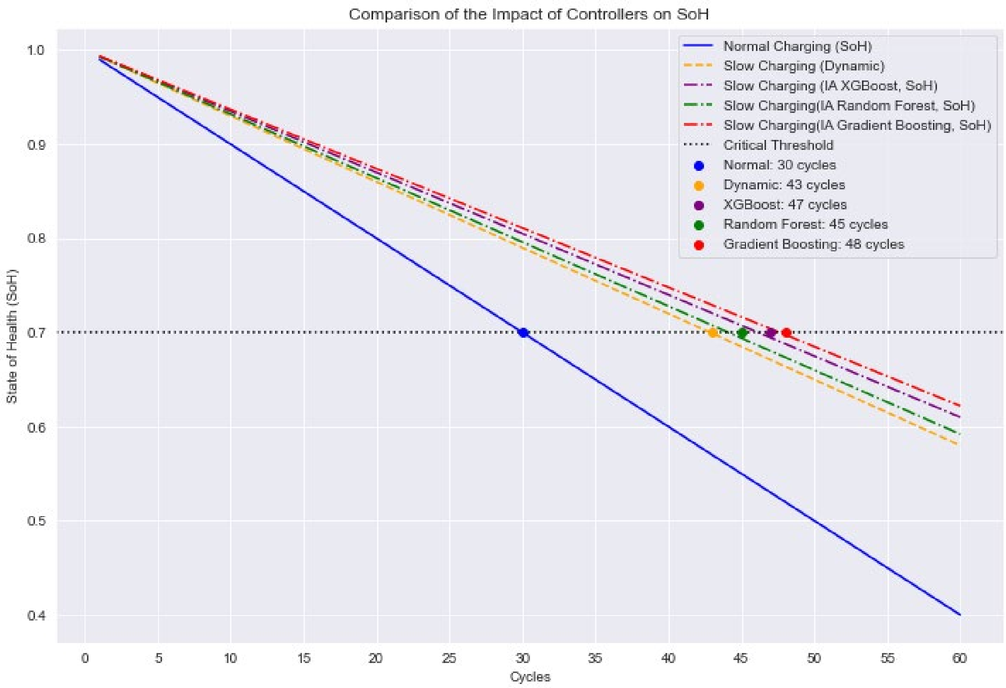

Fig. 8. Comparison of the impact of controllers on SoH

Rys. 8. Porównanie wpływu regulatorów na SoH baterii

current management keeps the battery in optimum operating conditions, prolonging its life and improving its long-term performance.

4.2. Impact of dynamic charge on SoH

The blue Normal Charge curve shows a more rapid, linear degradation of the battery's SoH, reaching the critical threshold of 0.7 SoH at the 30th cycle, at which point the battery is considered "end-of-life". In contrast, the orange Dynamic Charge curve illustrates a slower, more controlled degradation, thanks to the dynamic adjustment of current to battery conditions. This mechanism keeps the battery in better health for longer, delaying the reaching of the critical threshold. In fact, dynamic charging optimizes battery life by enabling more gradual degradation, with the critical threshold of 0.7 SoH reached after 43 cycles. The critical threshold is reached much sooner with normal charging, while dynamic charging extends the battery's effective life.

As the number of charge cycles increases, it becomes increasingly clear that normal charging accelerates battery degradation. In fact, normal charging, which applies a constant current regardless of variations in temperature, voltage, or SoH, leads to increased stress on the battery's internal components. This regular overcharging generates heat and voltage peaks that accelerate internal chemical reactions, leading to faster capacity loss. This deterioration shows up as a gradual drop in battery capacity as the number of cycles rises, which lowers efficiency and shortens service life. By avoiding difficult situations, dynamic charging, on the other hand, lessens this stress by adjusting the charging current in accordance with battery conditions (such as temperature, voltage, and SoH). In addition to shielding the battery from heat and chemical harm, this kinder current management significantly increases the number of useful cycles before the battery approaches its end of life. Dynamic charging prolongs the battery's lifespan and improves its overall performance in this manner.

4.3. Impact of dynamic and AI controllers on SoH

Battery charge management has been greatly enhanced by the addition of artificial intelligence (AI) controllers like Random Forest, XGBoost, and Gradient Boosting to the dynamic controller. By considering the intricate and ever-changing factors that affect battery health (SoH), such as temperature, voltage, and state of charge, this method seeks to make charge management even more accurate and flexible. By examining historical data trends, these AI models can forecast future battery behavior and proactively modify charging parameters to prevent overcharging or overheating situations.

Depending on the controllers employed, analysis of battery deterioration curves based on various charging procedures shows notable variations in SoH (State of Health) management. Without control, normal charging (blue curve) causes the battery to degrade quickly. A crucial threshold is crossed as early as cycle 30, which signals an early end of life. However, by postponing the crucial threshold to 43 cycles, slow charging using a dynamic controller (orange curve) extends battery life. This performance is further improved with the addition additional AI models (green, purple, and red curves). Random Forest model (green), which postpones the crucial threshold until cycle 45, XGBoost (purple) delays this threshold to 47 cycles, while Gradient Boosting (red) extends battery life to cycle 48, offering the best result of the three AI models. In conclusion, controllers based on AI models, in particular, Gradient Boosting, perform better than the traditional dynamic controller by considerably postponing the critical threshold, proving that they may maximize battery life far more effectively than standard charging, which is still the least effective technique.

5. Discussion

5.1. Piezoelectric battery life optimization

Optimizing the lifespan of batteries powered by piezoelectric generators hinges on precise, adaptive control of the charging current. Because piezo sources deliver low, intermittent power, the current must be matched to what the source and cell can safely accept. A dynamic controller operating under voltage/temperature limits and informed by SoH adjusts the current in small steps, easing it down when $T > 24°C$ or $V \rightarrow 4.2$ V, and raising it only after conditions return to nominal. As Figure 7 shows, this condition-aware charging delays the SoH = 0.7 threshold relative to normal charging, indicating lower electrochemical stress per cycle. By keeping voltage/temperature peaks and ripple low, the policy reduces thermal and parasitic-reaction stress, curbs efficiency losses, and postpones capacity fade. In practice, it turns the variability of the piezo source into a smooth, battery-friendly charge, improving energy capture without compromising safety. The result is longer service life and lower maintenance, particularly valuable for medical devices and compact renewable/IoT systems.

5.2. Optimizing battery life

The ring diagram clearly and concisely illustrates the impact of different control methods on battery life optimization. The Dynamic Controller (orange) increases battery life by 20.6% compared with normal charging, showing an interesting potential, despite its simplicity, for delaying the critical State of Health (SoH) threshold. The Random Forest AI (green) shows a significant increase of 23.8%, effectively exploiting supervised learning to predict degradation patterns. The XGBoost AI (purple), with an improvement of 27%, demonstrates its power in adaptive load cycle management. Last but not least, AI Gradient Boosting (in red) performs at its best, extending longevity by 28.6% because of its capacity to grasp intricate relationships between data.

This view demonstrates that the employment of dynamic controllers and sophisticated AI models is crucial for prolonging battery life, which is a tactical advancement in the optimization of storage systems, especially those driven by piezoelectric generators.

This study's primary goal is to extend battery life by postponing the point at which the batteries' State of Health (SoH) hits a crucial threshold. According to the findings, dynamic controllers and AI models work noticeably better than conventional charging techniques. By enabling adaptive responsiveness to battery requirements, dynamic controllers reduce current fluctuations and thermal stress. AI models also forecast battery behavior correctly, allowing for fine-tuning to avoid premature deterioration. Lifespan optimization poses particular difficulties

Battery Lifetime Optimization (%))

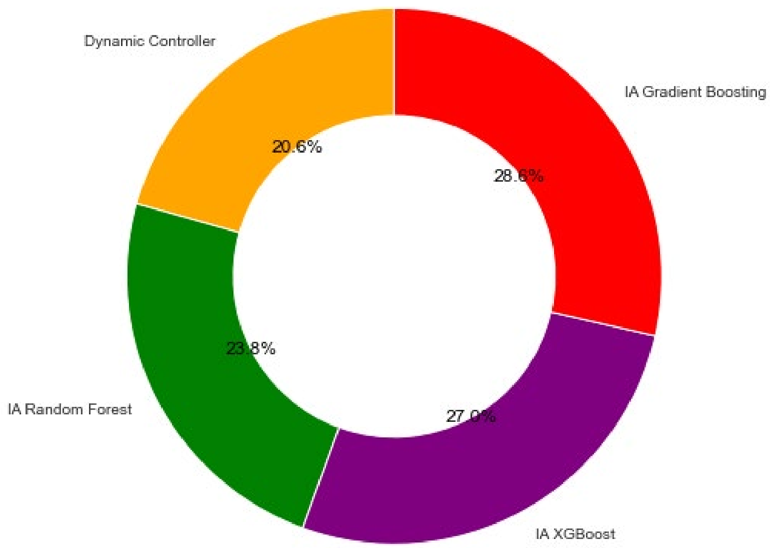

Fig. 9. Battery lifespan optimization

Rys. 9. Optymalizacja żywotności baterii

for batteries that are driven by piezoelectric generators. These generators put more strain on the batteries by producing sporadic, low-intensity loads. Dynamic controllers' flexibility is therefore crucial for modifying charge and discharge cycles in response to erratic energy flows. Furthermore, AI models are essential for precisely forecasting charging needs and preventing the quick deterioration brought on by improper cycling.

Systems powered by piezoelectric generators must optimize battery life in order to be reliable and durable. By incorporating dynamic controllers and AI models, these systems become more efficient, which lowers the cost of replacing batteries and limits their environmental impact. This approach opens the door to smart, sustainable energy systems that are supportive of cutting-edge applications in the Internet of Things (IoT), renewable energy, and autonomous technologies.

5.3. Comparison and analysis

Our findings on enhanced battery lifespan through dynamic charging and intelligent control align well with prior research. In this work, the dynamic logic-based charger improved cycle durability by 20%, and AI-driven controllers yielded up to 28.6% longer life compared to a standard approach (Figs 8 and 9). Similarly, other studies have reported substantial gains when moving away from simple constant-current profiles. For example, using realistic dynamic load profiles (instead of steady currents) was shown to extend cycle life by as much as 38% under EV-like conditions (Geslin et al. 2025). Another critical factor we examined is temperature, and our observations agree with previously documented thermal effects on aging. We found that battery voltage and health are strongly influenced by temperature changes (Figs 2 and 3), which aligns with the consensus that operating temperature is a key driver of degradation. Notably, controlled thermal conditions can be leveraged to improve longevity. For example, a study by INL showed that slightly increasing the cell temperature (by only 1–2°C) towards the end-of-life reduced internal resistance enough to deliver ~2000 additional cycles (about 3 extra months of operation) in a lithium iron phosphate cell (Garg et al. 2018) 1°C temperature increases extend the life of the cells by 2000 cycles (3 months of continuous cycling).

This illustrates how active thermal management can postpone failure in certain scenarios. However, it is also well established that higher temperatures accelerate side reactions and self-discharge, ultimately shortening cycle life if not kept in check. Thus, our approach of avoiding excessive heat and maintaining moderate temperatures is in line with best practices for battery longevity. Proper thermal management, as adopted in our experiments, helps prevent the rapid capacity fade that occurs outside the optimal temperature range, as noted by (Gaouzi et al. 2021) the state of charge (SoC). Beyond charge control and temperature, other contemporary studies likewise emphasize limiting battery stress to extend life. Researchers have shown that adjusting operating limits can yield significant benefits, for instance, raising the lower cutoff voltage as cells age resulted in ~16–38% longer lifetime in cycle tests by Zhu et al. (2023). This strategy is conceptually similar to our slow-charge method, as both aim to minimize deep discharge/charge extremes and thereby reduce strain on the electrodes. In general, mitigating aggressive conditions (high C-rates, extreme States of Charge, and high temperature) is a recurrent theme in battery aging research. Our work contributes to this literature by demonstrating that a combination of deferred (slow) charging, dynamic current adjustment, and machine-learning control can achieve notable improvements in SoH retention. In summary, the improvements we observed are well-supported by prior studies' results, strengthening the validity of our approach. By comparing our outcomes with these references, it is clear that intelligently managing charge profiles and environmental factors can consistently prolong lithium-ion battery life, which makes our proposed solution both effective and in harmony with the state-of-the-art.

Conclusion

This study set out to extend the service life of Li-ion cells powered by low, intermittent piezoelectric sources by aligning the charging policy with source constraints and battery health. From the temperature voltage analysis, we defined a safe operating window ($V \leq 4.2$ V, $T \leq 24$°C) and translated it into condition-aware control, a dynamic derating policy, and, further, AI controllers (Random Forest, XGBoost, Gradient Boosting) that choose the charging current to minimize predicted degradation under those same limits. Under the evaluated cycling conditions, the dynamic controller delayed the SoH = 0.7 threshold from 30 to 43 cycles, and the AI controllers extended it to 45, 47, and 48 cycles. These gains are explained mechanistically by lower voltage/temperature peaks and ripple, which curb parasitic reactions and heat-driven aging. The approach is directly applicable to piezo-powered biomedical and IoT devices where reliability and low maintenance are critical, and more broadly to systems where harvested power favors slow, condition-aware charging. Future work will validate the controllers with hardware-in-the-loop and real piezo front-ends, extend to other chemistries and environments, and pursue multi-objective control that balances longevity, charge time, and energy capture on resource-limited platforms.

The Authors have no conflicts of interest to declare.

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Optymalizacja żywotności baterii litowo-jonowych do urządzeń piezoelektrycznych przy użyciu kontrolerów dynamicznych i modeli sztucznej inteligencji

Streszczenie

Zasilanie małych urządzeń biomedycznych i urządzeń Internetu rzeczy za pomocą piezoelektrycznych urządzeń zbierających energię stanowi wyzwanie, ponieważ dostępna moc jest niska, przerywana i trudna do uregulowania. Może to w rzeczywistości nadmiernie obciążać elementy magazynujące energię, jeśli ładowanie nie jest odpowiednio dostosowane. W niniejszym badaniu oceniono trwałość baterii litowo-jonowych w takich warunkach, wykorzystując zbiory danych NASA PCoE i opracowując zasady ładowania dostosowane do ograniczonego źródła zasilania. Po pierwsze, badamy zachowanie temperatury i napięcia oraz identyfikujemy umiarkowany zakres roboczy, co motywuje do zastosowania podstawowego trybu powolnego ładowania, który zmniejsza obciążenie elektrochemiczne. Po drugie, wprowadzamy dwie warstwy sterowania: dynamiczny, oparty na regułach kontroler, który zmniejsza prąd, gdy napięcie na zaciskach zbliża się do 4,2 V lub temperatura przekracza 24°C w określonym bezpiecznym zakresie, oraz inteligentne kontrolery (Random Forest, XGBoost, Gradient Boosting), które przewidują stopniową degradację na podstawie rutynowo mierzonych sygnałów i wybierają prąd, który minimalizuje oczekiwane uszkodzenia w tych samych warunkach. Wykorzystując liczbę cykli do SoH = 0,7 jako punkt końcowy, sterowanie dynamiczne wydłuża żywotność z 30 do 43 cykli, podczas gdy inteligentne sterowniki osiągają 45, 47 i 48 cykli. Mechanizm ten wspierają zmniejszone szczyty napięcia i tętnienia oraz niższa ekspozycja termiczna. Ogólnie rzecz biorąc, dostosowanie powolnego, uwzględniającego stan i predykcyjnego ładowania do dostępności piezoelektrycznej znacznie wydłuża żywotność i poprawia wydajność pozyskiwania energii, umożliwiając tworzenie bardziej niezawodnych i wymagających mniej konserwacji systemów biomedycznych oraz systemów Internetu rzeczy.

Słowa kluczowe: optymalizacja żywotności akumulatorów litowo-jonowych, urządzenia piezoelektryczne, uczenie maszynowe, zasilanie urządzeń biomedycznych, sterowniki