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Battery cycle life and throughput optimization in wireless communication system with energy harvesting capability

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ABSTRACT

This research paper proposes a novel approach to address the energy challenges faced by internet of things (IoT) devices. The wireless communication system involves a transmitter equipped with energy harvesting module that charges both a rechargeable battery and a capacitor through an energy storage management system (ESMS). This ESMS is based on a reinforcement learning algorithm to dynamically switch between the battery and the capacitor, ensuring efficient power utilization. This reinforcement learning algorithm enables the device to learn and adapt its energy consumption patterns based on environmental conditions and usage, optimizing energy usage over time. Additionally, the system employs a rainflow counting method to estimate the state-of-health (SoH) of the battery, ensuring its longevity and overall system performance. By combining these approaches, the proposed system aims to significantly improve the energy efficiency and lifespan of IoT devices, as well as the amount of data sent for different temperature ranges, ultimately enhancing their cost-effectiveness and performance.

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1. INTRODUCTION

One of the main challenges in the internet of things (IoT) area lies in the need for energy wherever devices are installed, across all fields of application [1], [2]. This challenge is particularly pronounced for sensor nodes placed in inaccessible areas, such as biomedical sensors implanted in the human body, where battery replacement is exceedingly difficult. In such cases, battery life is crucial to ensure continuous power for these devices, exemplified by pacemakers and implantable defibrillators. To address this issue, significant attention has been given to renewable energies to extend the lifespan of batteries powering these devices. In this context, energy harvesting emerges as a highly promising solution, particularly for devices with lower energy consumption [3]. Combined with a hybrid storage system composed of batteries and capacitors, these systems are capable of powering wireless sensor networks (WSNs). Various topologies and configurations combining batteries and capacitors are discussed in [4], [5]. The key aspect involves the management of the storage system of the harvested energy based on the requirements and conditions of the IoT devices. Therefore, effective energy storage management systems (ESMS) must be employed [6], [7].

Since IoT devices require continuous power and most of them are battery-powered, they are facing finite battery life and high energy consumption, especially in inaccessible or hazardous locations. Energy harvesting technology addresses this by converting energy from sources like solar, thermal, wind, mechanical, pyroelectric, and RF into usable electrical energy, enhancing the efficiency, durability, and lifetime of IoT devices [8]. Several studies have addressed the problem of energy management in the IoT. In [9], the authors have proposed to minimize the volume of data that may be transmitted through the IoT environment and schedule the work of critical energy IoT nodes for better energy efficiency. Also, a fault tolerance scenario is applied to address the energy problems faced by IoT nodes. In [10], the authors proposed a reinforcement learning method to deal with the battery leakage for wireless communication systems. The research paper [11] addressed a set of algorithms that study energy management in the field of IoT. It listed the advantages and limitations of each one and raised a set of questions regarding the quality of services in the IoT and how to extend its lifespan from an energy perspective. Finally, it concluded by creating a comparative table between these algorithms. Another study relied on predicting the battery life of IoT devices using the random forest regression algorithm is proposed in [12]. The model is tested using the 'Beach Water Quality – Automated Sensors' dataset, which comes from sensors in an IoT network in Chicago, USA. The model incorporates various pre-processing techniques and achieves a predictive accuracy of 97% in predicting the battery life of IoT devices. In [13], a platform is introduced that combines sensing processing, and wireless communication features for low-power IoT based systems. It includes an energy management integrated circuit (IC) designed for highly efficient energy harvesting, making it ideal for low-power and compact energy sources. This platform accommodates various power supply options and integrates a hybrid energy storage system. An energy management strategy utilizing a reinforcement learning algorithm is outlined in [14]. This ESMS fulfills several stringent criteria, including low power consumption, high reliability, self-sufficiency in power supply, and data backup to handle unexpected failures. Energy is collected via solar panels and stored in supercapacitors. The developed system was applied to a physical ESMS device and tested in real-world conditions to gather practical data. A study explores multiple approaches to optimize energy systems and improve battery performance and lifespan is presented in [15]. It examines the power requirements for telecom site backups and evaluates the impacts of various parameters on battery life, proposing methods to optimize battery charging management for enhanced longevity and performance. In [16], an advanced forecasting model, such as long short-term memory (LSTM) and back propagation neural network (BPNN), are utilized to predict solar plant power output, demonstrating results closely aligned with actual power production. Dhaked and Birla [17] implemented a solar-thermal dish-Stirling system with battery storage in an islanded microgrid, integrating a control scheme to manage power. The system achieves 30% efficiency, reliably supplying energy in steady-state conditions, while the battery effectively supports the load during transient periods.

To address these issues, this paper proposes an energy harvesting system that explores the combination of capacitors and batteries to store energy and power sensor nodes. The rainflow algorithm is used to estimate battery life, while the reinforcement learning algorithm determines the optimal state of a wireless sensor node based on available energy, battery status, and information capacity during the designated transmission period. This approach helps adapt the model to a dynamic working environment and extend the battery lifespan.

The organization of this paper is as follows: The methods section provides a detailed description of the procedures followed in this work, including the justification for the chosen algorithm. This is followed by results and discussion section, where our findings and interpretations of the results are presented. Finally, the paper concludes with the conclusion section.

2. METHODS

A significant challenge within these ESMS is battery degradation due to deep discharge and high current demand [9]. High charge/discharge rates are influenced by the types and characteristics of batteries and capacitors [11], [12]. In this study, our focus is on wireless nodes of an IoT based system, assuming their transmitters are equipped with an energy recovery system. The collected energy can be stored either in the battery or in the capacitor via a pre-installed (see Figure 1). Communications occur within limited time intervals, with transmitters conducting transmissions over equal time durations, called time-slot and denoted as T_s. It is assumed that data packets arrive periodically and are transmitted in the subsequent time-slot T_s. A generated data packet is transmitted in the following time slot unless deemed unnecessary (e.g., for control applications). The transmission channel remains constant during each transmission period. Each node transmitter is equipped with an energy harvesting storage system and harvested energy is stored in either the battery or the capacitor and can be directly used for the next period, by a power management system based on the energy levels stored in both devices (battery/capacitor). The ESMS selects the appropriate storage unit, either the battery or the capacitor, depending on the remaining quantity of energy in each unit. Currently, most of the sensor nodes that are powered by harvested energy require a power management system (PMS) to adapt the stored energy to the related electronic circuits during various operations (such as processing and transmitting captured data). Indeed, the electrical energy provided by the energy harvester often exhibits unstable voltage, current, and power levels that are not directly suitable for supplying the electronic system.

Moreover, due to the intermittent nature of scavenged energy sources, the power management circuit must detect the harvested power level and potentially switch to an idle state when the quantity of power is insufficient (i.e., when the power consumed by the management circuit exceeds the scavenged power).

2.1. Energy harvesting

The renewable energy can be harvested from various external sources [18]. These sources are classified according to harvest-store-use and harvest-use [19]. The harvested energy is denoted as E_H. Since the presence of these energy sources is discontinuous in nature, electronic systems powered by energy harvesting must include a PMS and a storage device to store the scavenged energy. So, a conversion of the recovered energy is necessary to make it compatible and ready for use. Indeed, the usage of a transducer is essential to adapt the obtained energy to the usual storage device; the different transducers are mentioned in [20], [21]. The schematic of a typical mobile sensor system powered by energy harvesting is presented in Figure 2. The energy source is scavenged by the energy harvesting transducer and converted to electrical energy, even though it cannot be used in the actual form to power the electronic system.

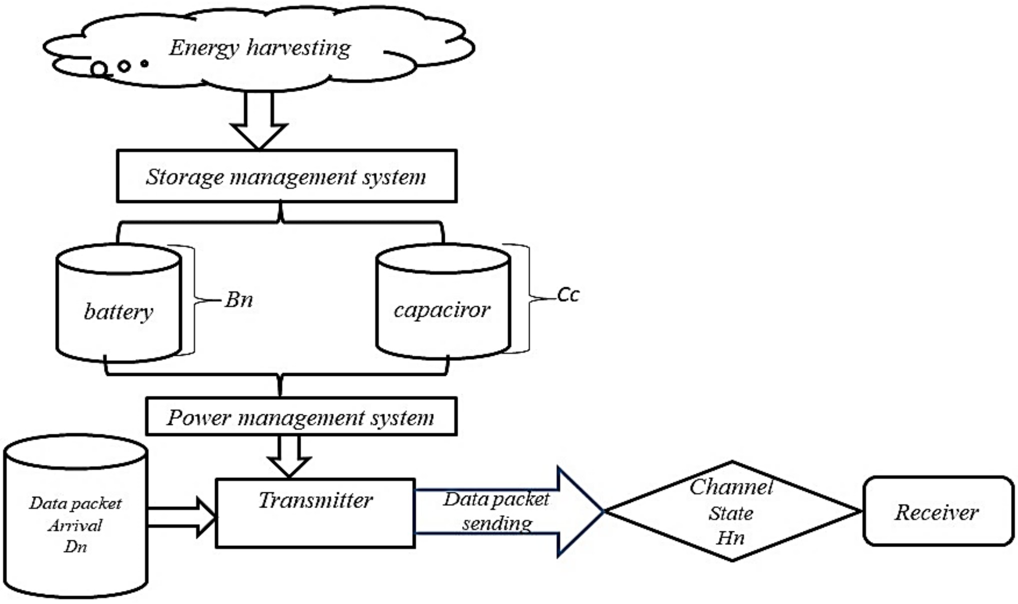

Figure 1. Storage and management system of energy harvesting

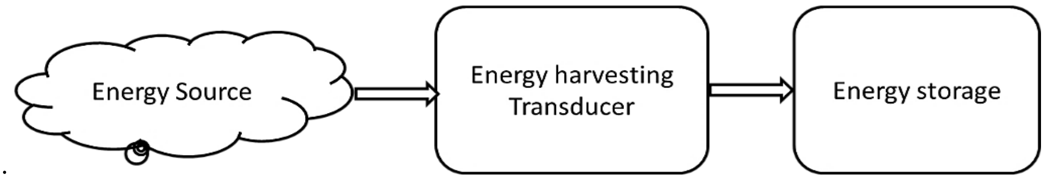

Figure 2. Energy harvesting management

2.2. Battery features analysis

In the field of the wireless sensor network, the battery is the cornerstone for continuity of service of connected objects in daily life, which makes the most critical components of any IoT deployment is the choice of batteries. That is why choosing the right battery for the smart device is a challenging task because it depends on several parameters [22]. Also, battery performance gets reduced by two sides, physical and chemical. Generally, the end of life for batteries is defined as 80% of the nominal capacity(i.e., the battery is considered as dead when it loses 80% of the nominal capacity). In general, the capacity of batteries fades mainly with the following stress factors [23], as the temperature, number of cycles of charge and discharge, the state of charge (SoC) swing, the C-rate, the waiting periods, and the SoC in waiting periods. The batteries are characterized by several parameters such as voltage and capacity. The voltage mainly depends on the SoC and the temperature of the battery, while the capacity represents the amount of charge delivered by the battery at the rated voltage. This relationship is explained in (1).

$$C = I^k . t \tag{1}$$

Where k is the Peukert exponent (typically k ϵ {1.0, 1.3} as stated in [24], C is the capacity, I is the discharge current, and t is the time at the minimum discharge. The battery SoC is defined as the percentage of the battery capacity available for discharge. It can be expressed as (2).

$$SOC = \frac{E_{bat}}{V_0 C_{bat}} \tag{2}$$

The capacity C_{bat} is measured in ampere-hours (Ah), V_0 is the battery voltage, and E_{bat} is energy of battery. Another parameter that is also important is the depth of discharge (DoD). It is defined as the percentage of the battery capacity that has been discharged.

$$DOD = \frac{C_{bat}.V - E_{bat}}{C_{bat}.V} \tag{3}$$

The SoC and DoD significantly affect battery life, along with other factors like operating time and temperature. SoC and DoD are the primary factors determining calendar and cycle aging of batteries. Calendar aging relates to capacity reduction over time, while cycle aging is linked to the frequency and depth of charge-discharge cycles [25]. Both types of aging are interrelated and crucial for understanding battery deterioration. In [26], [27], the authors give the batteries lose capacity over time and use. The capacity fade for calendar and cycle aging, respectively, is given as (4) and (5).

$$C_{f.cal}(t, T) = \alpha_t \times e^{\beta_t \times T} \times t^n \tag{4}$$

$$C_{f.cyc}(NC, T) = \alpha_{NC} \times e^{\beta_{NC} \times T} \times NC^n \tag{5}$$

The equations parameters are defined as follow: t is the time in month, T is the temperature in Kelvin, and NC is the number of cycles. The rest of parameters are coefficients for a lithium iron phosphate (LFP or LiFePO4) battery are as: $\alpha_t = 3.087.10^{-7}$, $\alpha_{NC} = 6.87.10^{-5}$, $\beta_t = 0.05146$, $\beta_{NC} = 0.027$, and $n = 0.5$. Recall that the main objective here is to estimate the lifetime of a battery by a suitable method. The rainflow-counting (RFC) algorithm is a useful method the estimate the battery cycles number [28]. RFC processes each SoC curve to return the experienced number of cycles at different DoD. Combining rainflow with the rule of Palmgren Miner [29], [30], the battery degradation during a given time period is expressed as (6).

$$D(\%) = \sum_{DoD=1}^{DoD=100} \sum \frac{N_{cyc}(DoD)}{N_{max}(DoD)} \tag{6}$$

Where D is the total damage that is when $D = 1$, the battery must be replaced. N_{cyc} is the number of cycles returned by the rainflow algorithm for each amplitude, the *DoD*, while the N_{max} is the number of cycles the battery can endure for each given *DoD*. According to the curves that gives the number of cycles versus the *DoD* provided by the datasheet of manufacturer for the battery VL30P cells type from SAFT batteries considered in this paper and based on [31], the number of cycles (N_{max} is reached if the capacity degradation attains 30%) can be approximated as (7).

$$N_{max}(\mathrm{DoD}) = 3.10^7 \times DoD(\%)^{-1.825} \tag{7}$$

The number of cycles can be calculated using the curve provided by the manufacturer of the VL30P battery, as shown in (8).

$$NC(80\%) = \frac{D(\%) \times 10000}{100\%} \tag{8}$$

By estimating the remained capacity of the battery at a percentage RC%, it will be possible to determine the end of life of the battery (EOL) in years as explained in (9).

$$1 - RC = \alpha_t \times e^{\beta_{t.T}} \times \left(\frac{yEOL}{12}\right)^n + \left[\alpha_{NC} \times e^{\beta_{NC.T}} \times NC^n\right] \times yEOL \quad (9)$$

The solution of (9) can expect the lifetime of the battery in years. The battery lifetime is calculated based on the steps illustrated in Algorithm 1.

Algorithm 1. Battery lifetime estimation process
Input:
- SOC vector (time series of state of charge)

Initialization:
- Set remaining capacity: RC ← 70%
- Estimate Ncycl (DOD) using rainflow counting (RFC) applied to SOC

Computation steps:
- Use equation (6) to compute the degradation percentage (D%)
- Replace D% into equation (8) to calculate the number of cycles (NC)
- Solve equation (9) to determine the battery lifetime

2.3. Capacitor features

Capacitors are highly versatile energy storage devices with applications in electric vehicles, energy harvesting, and grid stabilization, offering advantages like high power density, long lifecycle, and wide operating temperature range. Their key characteristics include nominal capacitance, working voltage, tolerance, leakage current, working temperature, polarization, and equivalent series resistance [32]. Capacitors have the potential to replace batteries due to their superior power density, which shortens charging times and longer life cycle [33]. They are forgiving when overused and environmentally friendly, making them ideal for IoT applications. Capacitors can serve as intermediate storage devices, providing power during battery changes or offline periods, and as uninterruptible power supplies (UPS) in emergencies. Additionally, hybrid applications combining capacitors with batteries can optimize energy usage and increase battery lifespan. The equivalent circuit of capacitor is shown in Figure 3.

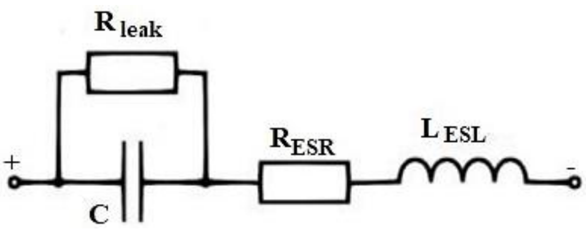

Figure 3. Equivalent circuit of capacitor

The lifespan of a capacitor is influenced by factors such as operating voltage and temperature [34], with leakage resistance R_{leak}, equivalent series resistance R_{ESR}, and equivalent series inductances L_{ESL} playing key roles. The dielectric in a real capacitor must have a high limited resistance to minimize current flow between the plates when voltage is applied. Leakage resistance typically ranges from 1 MΩ to 100 MΩ and can impact capacitor performance. Experimental tests and manufacturer data are essential for estimating capacitor lifespan. The Arrhenius equation is a key reference for predicting capacitor lifespan [35], with aging being influenced by operating conditions and temperature.

$$t_i = B \times e^{\frac{E_A}{K \times T_i}} \quad (10)$$

Where T_i is the absolute temperature in (Kelven), t_i is the reaction time for T_i in (h), B is the parameter to be determined (h), and E_A is the energy activation in eV. Whereas E_A is given by (11).

$$E_A = \frac{K \times \ln(\frac{t_1}{t_2})}{\frac{1}{T_1} - \frac{1}{T_2}} \quad (11)$$

The values of E_A is cited in [36], while K: empirical safety factor, defined as: If $T_0 = 105$ °C then for $I > I_0$, $K = 4$, and if $T_0 = 105$ °C, then for $I < I_0$, $K = 2$, also if $T_0 = 85$ °C then $K = 2$. In industry, the life of electrolytic capacitor is given in (12).

$$L = L_0 \times 2^{\frac{T_0 - T_{op}}{10}} \tag{12}$$

Where L is the life of the capacitor at the operating temperature T_{op} and L_o is the life at the rated temperature T_o. This means that for every 10 °C increase in operating temperature, the life of the electrolytic capacitor reduces by half [37]. The prediction of capacitor aging is often based on experimental extracts based on failure physics. According to Arrhenius' law, the lifespan of a capacitor is influenced by the ambient temperature, the current passing through it, and the applied electrical voltage. Capacitor manufacturers offer, in their catalogues, a formula to estimate the lifespan of capacitors (L) according to the various constraints [38].

$$L = L_0 \times K_T \times K_I \times K_V \tag{13}$$

With L_0 is the particular life (hours) in extreme operating conditions (maximum allowable temperature). While the other coefficients are K_T is the temperature factor and $\mathrm{K_T} = 2^{\frac{\mathrm{T_0 - T_c}}{10}}$ with T_0 is upper category temperature. The T_c is the ambient temperature in the application. K_I is the ripple current factor $K_i = K^{A\frac{\Delta T_0}{10}}$ with $A = 1 - (\frac{I_r}{I_0})^2$ and $I_r = \frac{I_{ri}}{1.4}$, where I_{ri} and I_r are respectively the ripple current in applications and the frequency-normalized ripple current, I_0 is the nominal ripple current at upper category temperature, and ΔT0 is core temperature increase of electrolytic capacitors. K_V is the voltage factor is expressed by $K_v = (\frac{V_0}{V_x})^n$, where V_0 and V_x are respectively the rated voltage and actual operating voltage. On the other hand, the exponent n can vary between 1 and 6, although for most datasheets cited in [38], [39]. The exponent is given by the following condition $0.5 \le \frac{V_0}{V_x} \le 0.8 \rightarrow n = 3$ and $0.8 \le \frac{V_0}{V_x} \le 1 \rightarrow n = 5$ cited in [40].

2.4. Energy storage management system

The proposed system aims to find optimal actions that lead to optimize data transmission and the battery lifetime as well. At each time slot denoted as n, the system decides about the storage destination (battery or capacitor), the transmission (transmit or not), and the source of energy if it decides to transmit. Figure 4 illustrates the topology of the proposed system.

The set of actions is as follows: i) $X_n^0 \in \{0,1\}$ is the indicator of the storage in the battery for $X_n^0 = 1$, in the capacitor for $X_n^0 = 0$ at the moment n; ii) The power source indicator is $X_n^1 \in \{0,1\}$ where $X_n^1 = 1$ indicates power from the battery and $X_n^1 = 0$ indicates power from the capacitor; and iii) The data transmission indicator is $X_n^2 \in \{0,1\}$ indicates the packet is dropped if $X_n^2 = 0$ or is transmitted if $X_n^2 = 1$. Powering the system with a battery combined with a capacitor directly influences the battery's lifespan, potentially reducing the number of cycles and increasing the quantity of data that can be transmitted. This optimization is illustrated in Figure 5.

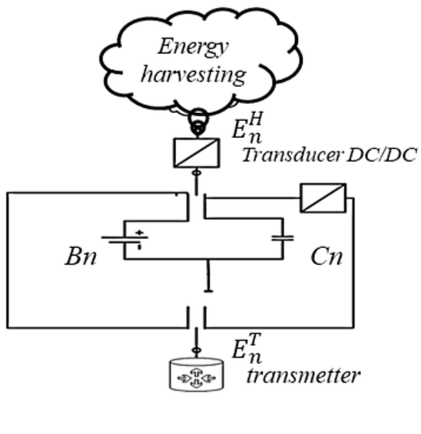

Figure 4. Synoptic energy model

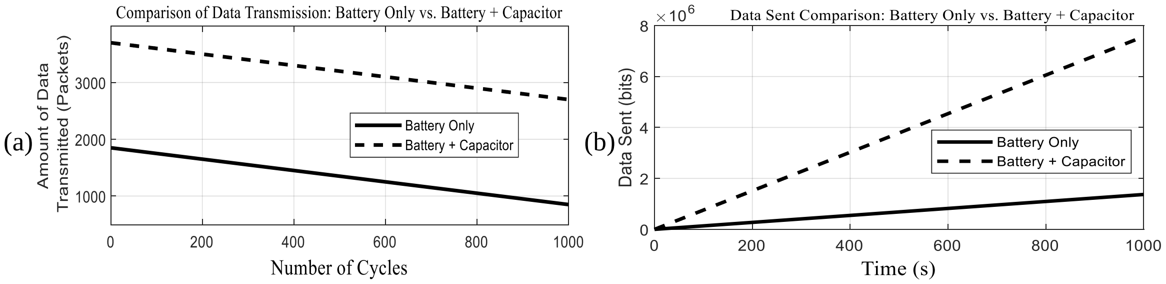

Figure 5. Comparison of a system with battery only vs. battery + capacitor: (a) data transmission comparison and (b) data sent comparison

In the following, energy optimization is addressed through the integration of reinforcement learning. The approach begins with the establishment of a system optimization framework, which serves as a foundation for intelligent control. Reinforcement learning is then leveraged to enhance the system's performance and adaptability.

2.4.1. Optimization and formulation system

The main goal is to increase the battery lifetime. It also aims to transmit the whole data without loss during the required time, as illustrated in (14).

$$\max_{\{X_i\}_{i=0}^{\infty}} \lim_{N\to\infty} \sum_{n=0}^{N} \gamma^n X_n D_n \tag{14}$$

Where $0 \leq \gamma < 1$ is the probability factor of the transmitter to accomplish its operation in the specified time slot. In real time the system checks the battery state B_n, the capacitor C_n, the size of data D_n, and the channel state. The system will estimate the amount of the required energy to transmit the incoming data, in order to select the used equipment to power the transmitter, this energy noted E_n^T must meet the following conditions:

$$X_n^0 . E_n^T \leq B_n X_n^1 + C_n(1 - X_n^1) \tag{15}$$

$$0 \leq B_n \leq B_{max} \tag{16}$$

$$0 \leq C_n \leq C_{max} \tag{17}$$

During each phase, the transmitter needs E_n^T amount of power to transmit data from B_n or C_n (in the battery or the capacitor). In the next epoch, the devices receive B_{n+1} or C_{n+1} amount of energy. Thus, this energy at each epoch can be updated (18) and (19).

$$B_{n+1} = min\{B_n - X_n^1 X_n^2 E_n^T + X_n^0 E_n^H, B_n^{max}\} \tag{18}$$

$$C_{n+1} = min\{C_n - (1 - X_n^1) X_n^2 E_n^T + (1 - X_n^0) E_n^H; C_n^{max}\} \tag{19}$$

The problem defined above is NP-hard since variables X_n^0, X_n^1, and X_n^2 are binary. Because the referenced problem has affine objective and constrained functions, it is considered as mixed integer linear program (MILP). Branch and Bound is a commonly used algorithm to solve this kind of problems [41]. However, to use this algorithm, all the future data, channel state and energy arrivals must be known in advance. In the literature lot of works were proposed to solve MILP based on machine learning and reinforcement learning is a powerful solution to deal with such this style of problem [42].

2.4.2. Reinforcement learning

Reinforcement learning (RL) is proposed as a solution for energy optimization in point-to-point wireless communication. The method involves an energy management system that dynamically optimizes power flow between batteries and capacitors in IoT communication systems. This approach learns optimal decisions over time without prior knowledge of energy demands, using only environmental state observations (e.g., battery cycles and lifetime). Basically, RL system is modeled by the interaction between environment and the model components as illustrated in Figure 6.

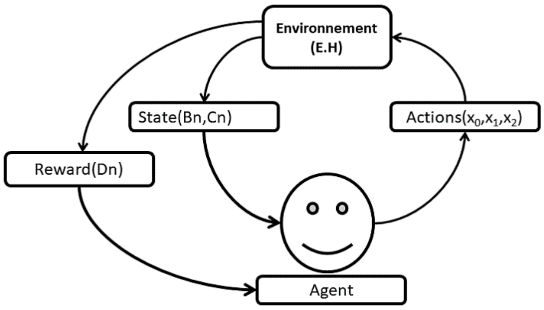

Figure 6. Reinforcement learning and interaction model

Q-learning is a value based learning algorithm in reinforcement learning. The main objective of reinforcement learning is to determine the best Q-value for each state using a learning rate coefficient α_n in the nth learning iteration and a discount factor $0 \leqslant \gamma \leqslant 1$. This approach ensures that the transmitter has a probability of $1 - \gamma$ to operate successfully in each time slot Ts.

$$Q_n(s_j, x_i) = (1 - \alpha_n) Q_{n-1}(s_j, x_i) + \alpha_n \left[R_{xi}(s_j, s_k) + \gamma\, max_{xj\in A}\, Q_{n-1}\,(s_k, x_j) \right] \tag{20}$$

The used q-learning notations are:
- The state set S<B_n, H_n, C_n, D_n>, where B_n represents the battery energy at the moment n, H_n is the state of channel, C_n represents the capacitor energy at the moment n, and D_n amount of collected data in the time period n.
- Set of actions A={$< X_n^0, X_n^1, X_n^2 >$}.
- The reward function is explained by the following function: $R_t(S_n, S_{n+1}) = X_n D_n$.

Algorithm 2 represents the pseudo-code of the Q-learning algorithm.

Algorithm 2. Q-learning algorithm
Initialization
- For each state $S_i \in S$ and each action $x_j \in A$, do:
  $Q(S_i, x_j) \leftarrow 0$
- Evaluate the initial state $S_i \in S$

Learning process
While the maximum number of iterations is not reached, do:
- Choose an action $x_j \in A$ using the ε-greedy policy based on the current Q-values.
- Execute action x_j and observe:
  – The immediate reward R_t
  – The next state S′
- Update the Q-value using the Q-learning update rule:
  $Q_{t+1}(S_i, x_j) \leftarrow Q(S_i, x_j) + \alpha\, [R_t + \gamma\, max_{x,J}\, Q_t(S', x'_j) - Q(S_i, x_j)]$
- Set the current state: $S_i \leftarrow S'$

End while

The Q-learning algorithm determines the optimal state by estimating the next Q-value, Q_{n+1} (Si, xi). This estimation is achieved by combining the previous estimate, Qn-1 (Si, xi), with the estimated expected value of the best action at the subsequent state Sn+1. During each time slot (T_S), the algorithm refines its estimates according to the following steps:
- Notices the current state $S_n = S_j \epsilon$ S.
- Selects and executes an action $X_n = x_i \epsilon$ A.
- Observes the next state and the corresponding reward, then updates its estimate of Q using (20).

3. RESULTS AND DISCUSSION

The simulation analysis of the proposed method is presented in this section. The parameters used in this work are as follows: The system model has a maximum energy capacity of battery that is located in Bmax = {20. 2.5×10^{-5}, 50. 2.5×10^{-5},100. 2.5×10^{-5}}J. The energy level in the battery is Bn = {0, Bmax}. The packet sizes are D = {300, 600} bits with transition state probabilities pd (d1, d1) = pd (d2, d2) = 0.99 and the channel state Hn = {0.01 0.02}. The energy harvested in time-slotted Ts = 100 s, which is worth is

$E_n^T = 0.5\times10{-5}$ J. The noise power density is N0 = −167 dBm/Hz, the transmit time is ΔTx = 0.005 s. The capacitor capacity ranges from 0 to 240 μF. The Q-learning parameters are: the learning rate fixed at α = 0.85, the exploration probability is ε = 0.1, and the discount factor γ = 0.99.

Figure 7 depicts the expected transmitted data by the system as a function of the capacitor capacity at different temperature values. Despite the temperature parameter directly influencing the degradation of battery capacity, however, the proposed method demonstrates that the quantity of transmitted data increases with the capacity of the capacitor. Notably, beyond a certain capacity value, the data transmission becomes almost linear.

Figure 8 illustrates the increase in battery capacity as a function of capacitor capacity at different temperature values, demonstrating the effectiveness of the proposed model. The battery's lifetime increases linearly before stabilizing with a slight augmentation. This indicates that the method used in this system optimizes the battery's lifespan by comparing it with other solutions involving only the battery, without the inclusion of a capacitor or the reinforcement learning algorithm mentioned earlier.

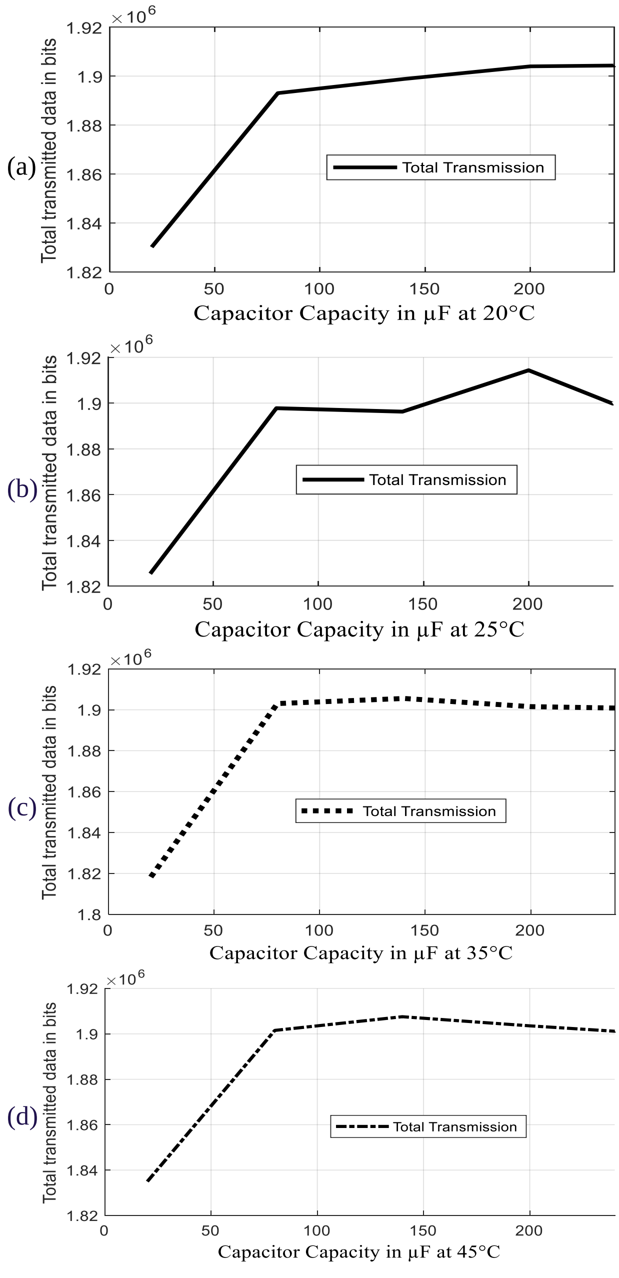

Figure 7. The amount of data transmitted with the proposed method at different temperature values: (a) 20 °C, (b) 25 °C, (c) 35 °C, and (d) 45 °C

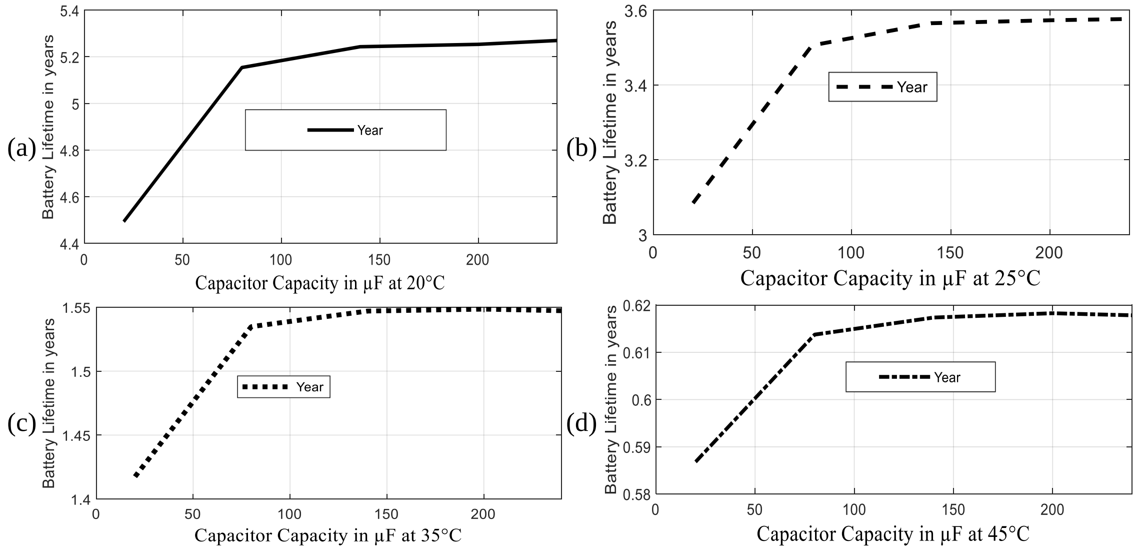

Figure 8. The lifetime of the battery with the proposed method for different temperature values, in function the capacity of the capacitor: (a) 20 °C, (b) 25 °C, (c) 35 °C, and (d) 45 °C

Our numerical results have illustrated the relevance of the learning theoretic approach for practical scenarios. The proposed model leads to an improvement in the quantity of data transmitted without being influenced by temperature. This method enhances the effectiveness of the communication system equipped by a device of energy harvesting and stores its energy in a battery or a capacitor, alongside a reinforcement learning algorithm. This adaptation of transmitted data surpasses the performance of the previous systems. As for the battery-capacitor combination for energy storage, this ESMS have expanded the battery lifespan by reducing the charge discharge cycles. Unlike the approach presented in [9], which focuses on reducing data transmission to enhance energy efficiency, our method increases data transmission through the utilization of a hybrid storage system. Additionally, our online optimization model demonstrates superior performance compared to offline regression algorithms, particularly in dynamic environments where pre-processing is necessary [12]. Offline models often require updates when environmental conditions change, whereas our approach adapts to the environment.

The proposed system effectively meets its objectives by optimizing energy efficiency through two key strategies. First, it extends the battery lifespan by implementing advanced energy management techniques, which reduce the rate of battery degradation and improve overall longevity. Second, it enhances data transmission capabilities by leveraging a hybrid storage system that balances performance and efficiency. This dual approach not only ensures that energy consumption is minimized but also that a greater volume of data can be transmitted without compromising system performance. As a result, the system achieves a robust balance between maintaining high energy efficiency and meeting data transmission needs, providing a sustainable solution that adapts to varying operational demands.

4. CONCLUSION

In this paper, an energy harvesting system is proposed to explore the combination of capacitors and batteries to store harvested energy and then power a wireless transmitter node. The rainflow algorithm estimates battery life, while the Q-learning algorithm determines the optimal strategy, to transmit data or to store gathered energy in a node based on the available energy, battery state, and the channel information during the designated transmission period. Our results demonstrate the applicability of the approach proposed to extend the battery lifespan by implementing advanced energy management techniques, which reduce the rate of battery degradation and improve overall longevity and enhances data transmission capabilities by leveraging a hybrid storage system that balances performance and efficiency. This dual approach not only ensures that energy usage is optimized but also that a greater volume of data can be transmitted without compromising system performance. Future studies could follow up on work done with real-world deployments to validate the theoretical models and optimization algorithms proposed under different environmental and operational conditions. In addition, machine learning models possibly trained on operational data could predict energy availability, allowing transmission schedule optimization to become more dynamic and potentially improving system performance. Also, examining how energy harvesting and battery management techniques could empower these emerging paradigms, such as massive machine-type communication (mMTC), will also create opportunities for scalable and efficient wireless communication networks.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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