Integrating Energy Harvesting within the IoT Ecosystem for Sustainable Wireless Communication

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Abstract

The Internet of Things (IoT) leads technological advancements across diverse sectors, ranging from smart healthcare to intelligent transportation. However, rapid development of IoT devices with increasing energy demands have raised concerns about reliance on conventional, limited-life batteries. The use of conventional batteries in IoT devices brings various drawbacks, including high maintenance costs, frequent battery replacements, and environmental concerns. Moreover, the energy crisis highlights the urgency of ensuring technology sustainability, particularly within the IoT paradigm. A promising solution to tackle these challenges involves integrating Energy Harvesting (EH) technologies into IoT systems, reducing the need for frequent battery replacements, extending operational life of these devices, and diminishing the negative effect on the environment.

Nevertheless, the peculiarities of EH technologies and the varying energy requirements of IoT systems present new challenges. This complex integration demands adaptations across multiple layers of the IoT protocol stack, primarily focusing on the energy-intensive Medium Access Control (MAC) layer operations. Despite its key role in optimizing energy consumption within IoT systems, there is a noticeable gap in the literature regarding systematic MAC layer enhancements for EH integration. These enhancements may be particularly relevant in critical applications like IoT medical devices.

This dissertation presents a comprehensive framework for assessing energy consumption across diverse wireless technologies, focusing on MAC operation perspectives. This innovative framework provides valuable insights for choosing appropriate EH solutions adapted to specific communication technologies within Wi-Fi-based IoT systems.

Throughout our research, we perform simulations in a densely deployed solar-powered Wi-Fi network operating in an e-healthcare environment. Our main goal is to ensure that Quality of Service (QoS) requirements are met within a QoS limited environment, while minimizing the network's energy usage. To achieve this, we fine-tune the

Contention Window (CW) initialization and introduce an optimization algorithm which considers the Access Point (AP) coordination. Our approach draws inspiration from the forthcoming IEEE 802.11bn amendment, which discusses AP coordination method.

Finally, we leverage Reinforcement Learning (RL) methods to further strengthen this approach to effectively adapt to the complexity and dynamic behavior of the network. The innovative RL algorithms we propose for MAC layer parameters effectively reduce the energy consumption of the network compared to traditional Wi-Fi setups, while ensuring the QoS for e-healthcare applications is maintained. Furthermore, we show that more energy can be conserved within the network by fine-tuning MAC layer parameters. This highlights the potential for reducing the size of solar cells while increasing the adaptability of EH techniques for IoT devices. Lastly, we implement a sleep/wake-up strategy, which significantly reduces network energy consumption which may impact QoS requirements.

The main contribution of this dissertation is to improve the energy efficiency in IoT systems through passive technologies such as EH methods. We conclude that this work can help researchers in academia and industry to understand the current state-of-the-art of EH MAC protocols for IoT, improve the early adoption of EH MAC layer protocols in IoT systems, and new possibilities for IoT EH integration, particularly in contexts with restricted QoS environments such as e-Healthcare.

Resumen

El Internet de las cosas (IoT, de sus siglas en inglés) lidera los avances tecnológicos en diversos sectores, desde la atención sanitaria inteligente hasta el transporte inteligente. Sin embargo, el rápido desarrollo de dispositivos IoT con demandas de energía crecientes ha suscitado preocupación por la dependencia de baterías convencionales de vida limitada. El uso de baterías convencionales en dispositivos IoT conlleva varios inconvenientes, incluidos los altos costos de mantenimiento, reemplazos frecuentes de baterías y problemas ambientales. Además, la crisis energética destaca la urgencia de garantizar la sostenibilidad tecnológica, especialmente dentro del paradigma IoT. Una solución prometedora para abordar estos desafíos consiste en integrar tecnologías de captación de energía (EH, de sus siglas en inglés) en los sistemas IoT, reduciendo la necesidad de sustituir las baterías con frecuencia, prolongando la vida útil de estos dispositivos y disminuyendo el efecto negativo en el medio ambiente.

Sin embargo, las peculiaridades de las tecnologías de EH y los diversos requisitos de energía de los sistemas IoT presentan nuevos desafíos. Esta compleja integración exige adaptaciones en múltiples capas de la pila de protocolos IoT, centrándose principalmente en las operaciones de la capa de control de acceso al medio (MAC, de sus siglas en inglés) que consumen mucha energía. A pesar de su papel clave en la optimización del consumo de energía dentro de los sistemas IoT, existe una brecha notable en la literatura con respecto a las mejoras sistemáticas de la capa MAC para la integración de EH. Estas mejoras pueden ser particularmente relevantes en aplicaciones críticas como los dispositivos IoT médicos.

Esta disertación presenta un marco integral para evaluar el consumo de energía en diversas tecnologías inalámbricas, centrado en la perspectiva de operación de la capa MAC. Este marco innovador proporciona información valiosa para elegir soluciones de EH adecuadas, adaptadas a tecnologías de comunicación específicas dentro de sistemas IoT basados en Wi-Fi.

A lo largo de esta investigación, se han realizado simulaciones en redes Wi-Fi densas alimentadas con energía solar, implementadas en un entorno de e-salud. El objetivo principal ha sido garantizar que se cumplan los requisitos de calidad del servicio (QoS, de sus siglas en inglés) dentro de un entorno de QoS limitado, a la vez que se minimiza el uso de energía de la red. Para lograrlo, se ha ajustado la inicialización de la ventana de contención (CW, de sus siglas en inglés) y se ha introducido un algoritmo de optimización que considera la coordinación del punto de acceso (AP, de sus siglas en inglés). El enfoque de esta investigación se inspira en la próxima enmienda IEEE 802.11bn, que propone el método de coordinación de AP.

Por último, se aprovechan los métodos de aprendizaje por refuerzo (RL, de sus siglas en inglés) para fortalecer aún más este enfoque, y adaptarse de forma efectiva a la complejidad y el comportamiento dinámico de la red. Los innovadores algoritmos de RL que se proponen para los parámetros de la capa MAC reducen eficazmente el consumo de energía de la red en comparación con las configuraciones de Wi-Fi tradicionales, al tiempo que garantizan que se mantenga la QoS para las aplicaciones de e-salud. Además, se demuestra que se puede conservar más energía de la red ajustando los parámetros de la capa MAC. Esto destaca el potencial de reducir el tamaño de las celdas solares, a la vez que aumenta la adaptabilidad de las técnicas de EH para los dispositivos IoT. Por último, se implementa una estrategia de dormir/despertar, que reduce significativamente el consumo de energía de la red, lo que puede afectar los requisitos de QoS.

La principal contribución de esta disertación es mejorar la eficiencia energética en los sistemas IoT a través de tecnologías pasivas como los métodos de EH. Concluimos que este trabajo puede ayudar a los investigadores del ámbito académico y de la industria a comprender los nuevos protocolos MAC de EH para IoT, mejorar la adopción temprana de protocolos de capa MAC de EH en sistemas IoT, y aportar nuevas posibilidades para la integración de EH en IoT, especialmente en contextos con entornos de QoS restringidos como la e-salud.

Resum

La Internet de les Coses (IoT, de les seves sigles en anglès) lidera els avanços tecnològics en diversos sectors, des de l'atenció sanitària intel·ligent fins al transport intel·ligent. No obstant això, el ràpid desenvolupament de dispositius IoT amb demandes d'energia creixents ha suscitat preocupació per la dependència de bateries convencionals de vida limitada. L'ús de bateries convencionals en dispositius IoT comporta diversos inconvenients, inclosos els alts costos de manteniment, reemplaçaments freqüents de bateries i problemes ambientals. A més, la crisi energètica destaca la urgència de garantir la sostenibilitat tecnològica, especialment dins del paradigma IoT. Una solució prometedora per a abordar aquests desafiaments consisteix a integrar tecnologies de captació d'energia (EH, de les seves sigles en anglès) en els sistemes IoT, reduint la necessitat de substituir les bateries amb freqüència, prolongant la vida útil d'aquests dispositius i disminuint l'efecte negatiu en el medi ambient.

No obstant això, les peculiaritats de les tecnologies d'EH i els diversos requisits d'energia dels sistemes IoT presenten nous desafiaments. Aquesta complexa integració exigeix adaptacions en múltiples capes de la pila de protocols IoT, centrant-se principalment en les operacions de la capa de control d'accés al medi (MAC, de les seves sigles en anglès) que consumeixen molta energia. Malgrat el seu paper clau en l'optimització del consum d'energia dins dels sistemes IoT, existeix una escletxa notable en la literatura respecte a les millores sistemàtiques de la capa MAC per a la integració d'EH. Aquestes millores poden ser particularment rellevants en aplicacions crítiques com els dispositius IoT mèdics.

Aquesta dissertació presenta un marc integral per a avaluar el consum d'energia en diverses tecnologies sense fils, centrat en la perspectiva d'operació de la capa MAC. Aquest marc innovador proporciona informació valuosa per a triar solucions d'EH adequades, adaptades a tecnologies de comunicació específiques dins de sistemes IoT basats en Wi-Fi.

Al llarg d'aquesta recerca, s'han realitzat simulacions en xarxes Wi-Fi denses alimentades amb energia solar, implementades en un entorn d'e-salut. L'objectiu principal ha estat garantir que es compleixin els requisits de qualitat del servei (QoS, de les seves sigles en anglès) dins d'un entorn de QoS limitat, alhora que es minimitza l'ús d'energia de la xarxa. Per a aconseguir-ho, s'ha ajustat la inicialització de la finestra de contenció (CW, de les seves sigles en anglès) i s'ha introduït un algorisme d'optimització que considera la coordinació del punt d'accés (AP, de les seves sigles en anglès). L'enfocament d'aquesta recerca s'inspira en la propera esmena IEEE 802.11bn, que proposa el mètode de coordinació d'AP.

Finalment, s'aprofiten els mètodes d'aprenentatge per reforç (RL, de les seves sigles en anglès) per a enfortir encara més aquest enfocament, i adaptar-se de manera efectiva a la complexitat i el comportament dinàmic de la xarxa. Els innovadors algorismes de RL que es proposen per als paràmetres de la capa MAC redueixen eficaçment el consum d'energia de la xarxa en comparació amb les configuracions de Wi-Fi tradicionals, al mateix temps que garanteixen que es mantingui la QoS per a les aplicacions d'e-salut. A més, es demostra que es pot conservar més energia de la xarxa ajustant els paràmetres de la capa MAC. Això destaca el potencial de reduir la mida de les cel·les solars, alhora que augmenta l'adaptabilitat de les tècniques d'EH per als dispositius IoT. Finalment, s'implementa una estratègia de dormir/despertar, que redueix significativament el consum d'energia de la xarxa, la qual cosa pot afectar els requisits de QoS.

La principal contribució d'aquesta dissertació és millorar l'eficiència energètica en els sistemes IoT a través de tecnologies passives com els mètodes d'EH. Concloem que aquest treball pot ajudar als investigadors de l'àmbit acadèmic i de la indústria a comprendre els nous protocols MAC d'EH per a IoT, millorar l'adopció primerenca de protocols de capa MAC d'EH en sistemes IoT, i aportar noves possibilitats per a la integració d'EH en IoT, especialment en contextos amb entorns de QoS restringits com l'e-salut.

This book is dedicated to everyone who has lost loved ones in the COVID-19 pandemic. May science and technology one day prevent such crises.

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List of Abbreviations

3GPP 3rd Generation Partnership Project

A-MAC Adaptive MAC

AC/DC Alternating Current/Direct Current

ACK Acknowledgement

AESC Acoustoelastic Sonic Crystal

AH-MAC Adaptive Hierarchical MAC

AI Artificial Intelligence

AID Association IDentifiers

AIFS Arbitration Inter-Frame Spacing

AO-ALOHA Adaptive-Opportunistic ALOHA

AP Access Point

AT-MAC Adaptive TDMA MAC

BER Bit Error Rate

BITXOP Bi-Directional Transmission Opportunity

BLE Bluetooth Low Energy

BSS Basic Service Set

CCA Clear Channel Assessment

CDMA Code Division Multiple Access

CKN Connected K-Neighbourhood

CL-EHSN Cross-Layer MAC Energy Harvesting Sensor Node

CoAP Constraint Application Protocol

Cooperative Energy Harvesting MAC CEH-MAC

CPU-memory Central Processing Unit-memory

LIST OF ABBREVIATIONS

CSMA Carrier Sensing Multiple Access

CSMA/CA Carrier Sensing Multiple Access with Collision Avoidance

CSMA/CD Carrier Sensing Multiple Access with Collision Detection

CW Contention Window

DCF Distributed Coordination Function

DDPG Deep Deterministic Policy Gradient

DFA Dynamic Frame ALOHA

DFSA Dynamic-FSA

DIFS Distributed Inter-Frame Space

DQL Deep Q-Learning

DQN Deep Q-Network

DRL Deep Reinforcement Learning

DS-CDMA Direct-Sequence Code Division Multiple Access

DSP Duty-cycle Scheduling based on Prospective increase in residual energy

DSR Duty-cycle Scheduling based on Residual energy

DSSC Dye Sensitized Solar Cell

DSSS Direct-Sequence Spread Spectrum

Dynamic TDMA D-TDMA

e-Health Electronic Health

EA-MAC Energy Adaptive MAC

EC-GSM Extended Coverage Global System for Mobile communication

ECG Electrocardiogram

ED-MAC Exponential Decision MAC

EDCA Enhanced Distributed Channel Access

eDRx Extended Discontinuous Reception

EEG Electroencephalography

EEM-EHWSN Enhanced Energy Management scheme in Energy Harvesting Wireless Sensor Networks

EG-DFA-MAC Energy-Group based DFA

EH Energy Harvesting

EH-MAC Energy Harvesting MAC

EH-RDFSA Energy Harvesting aware Reservation Dynamic Frame Slotted-ALOHA

EH-TDMA Energy Harvesting TDMA

EL-MAC Energy-Level MAC

EMR Electronic Medical Record

ENAN Estimated Number of Active Neighbors

End-to-End delay E2E delay

ENO Energy Neutral Operation

EPC Gen2 Electronic Product Code Class 1 Generation 2

ER Energy Request

ERI-MAC Energy-harvested Receiver-Initiated MAC

EWMA Exponentially Weighted Moving-Average

FA Frame ALOHA

FDMA Frequency Division Multiple Access

FER Frame Error Rate

FPGA Field Programmable Gate Array

FSA Frame Slotted ALOHA

FSR Frame Successful Rate

FTDMA Frequency and Time Division Multiple Access

GTS Guaranteed Time Slot

H-MAC Hybrid MAC

HARQ Hybrid Automatic Repeat Request

HE-MAC Harvest-then-transmit-based Enhanced DCF MAC

HE-MAC Harvested Energy-Adaptive MAC

HEAP-EDF-MAC Powered by Ambient Energy Harvesting-Earliest Deadline First polling MAC

HEH-BMAC Human Energy Harvesting for WBANs

HM-RIMAC Hybrid Multi-layer-Receiver-Initiated MAC

ICTs Information and Communication Technologies

ID Polling Identity Polling

LIST OF ABBREVIATIONS

IEEE Institute of Electrical and Electronics Engineers

Ifs Inter frame space

IoT Internet of Things

ISO/IEC International Organization for Standardization/International Electrotechnical Commission

JD Joint Decoding

KPIs Key Performance Indicators

LEACH Low Energy Adaptive Clustering Hierarchy

LEB-MAC Load and Energy Balancing MAC

LESOP-MAC Low Energy Self-Organizing Protocol

Li-Ion Battery Lithium Ion Battery

loRaWAN Long Range Wide Area Network

LPL Low Power Listening

LPWAN Low-Power Wide Area Network

LTE Long Term Evolution

LTE-M Long Term Evaluation for Machines

M2M Machine to Machine

MAB Multi-Armed Bandit

MAC Medium Access Control

MARL Multi-Agent Reinforcement Learning

MCS Modulation and Coding Scheme

MIMO Multi input Multi output

MIoT Medical IoT

ML Machine Learning

MLMAC-HEAP Multi Layer MAC Protocol Powered by Ambient Energy Harvesting

mmWave millimeter wave

MQAM M-Ary Quadrature Amplitude Modulation

MQTT Message Queue Telemetry Transport

MTPP-MAC Multi-Tier Probabilistic Polling MAC

MU-MIMO Multi-User Multiple Input, Multiple Output

NACK Negative Acknowledgment

NB-IoT Narrow Band-IoT

NFC Near-Field Communication

NICs Network Interface Cards

NOMA Non-Orthogonal Multiple Access

ns-3 Network Simulator-3

OD-MAC On-Demand MAC

OER-MAC On-Demand Energy Requesting MAC

OFDMA Orthogonal Frequency Division Multiple Access

OHCA Orthogonal Frequency Division Multiple Access-based Hybrid Channel Access

OMNeT Objective Modular Network Testbed

OOK On-Off Keying

OPDMA Orthogonal Power Division Multiple Access

OPNET Optimized Network Engineering Tools

OPS Opportunistic Power Save

OPWUM Opportunistic Wake-Up MAC

OSI Open System Interconnection

PDR Packet Delivery Ratio

PEGASIS Power Efficient Gathering in Sensor Information Systems

PHY Physical

PHYCCA Physical Clear Channel Assessment

PLoRa Passive Long-Range MAC

PLR Packet Loss Ratio

PN Pseudo-Noise

PP-MAC Probabilistic Polling MAC

PS-EHWSN MAC) Preamble Sampling scheme based MAC protocol for Energy Harvesting WSNs

PSM Power Saving Mode

QAEE-MAC Quality of Service-Aware Energy-Efficient MAC

QoE Quality of Experience

LIST OF ABBREVIATIONS

QoS Quality of Service

QPPD-MAC QoS MAC Protocol for Prioritized Data

RACH Random Access Channel

RAW Restricted Access Window

REACH-MAC RF Energy Auto-Charging and Harvesting MAC

RF Radio Frequency

RF-AASP Radio Frequency-based Adaptive Active Sleeping Period

RF-MAC Radio Frequency MAC

RFID Radio Frequency Identification

RFTDMA Random Frequency and Time Division Multiple Access

RICER Receiver Initiated Cycled Receiver

RIH-MAC Receiver-Initiated Harvesting-aware MAC

RL Reinforcement Learning

RRM Radio Resource Management

RSSI Received Signal Strength Indicator

RTR Ready to Receive

RTS/CTS Request To Send/Clear To Send

SAN Slotted ALOHA-Non-Orthogonal Multiple Access

SC-FDMA Single Carrier Frequency Division Multiple Access

SEHEE-MAC Solar Energy Harvesting Energy-Efficient MAC

SIC Successive Interference Cancellation

SP Service period

STDMA Spatial Time Division Multiple Access

SyWiM Synchronized Wake-up interval MAC

TBB Token Bus

TDMA Time Division Multiple Access

TEG Thermometric Generator

TGax Task Group 802.11ax

TICER Transmitter Initiated Cycled Receiver MAC

TIM Traffic Indication Map

TPGFPlus Two-Phase Geographic Greedy Forwarding

TR-EH-TDMA-MAC Time-Resue Energy Harvesting TDMA

TSCH Time Slotted Channel Hopping

TWT Target Wake-up Time

Tx/Rx Transmit/Receive

TXOP Transmission Opportunity

UE User Equipment

UNB Ultra-Narrow Band

WCMA Weather Conditioned Moving Average

WEH Wireless Energy Harvesting

Weightless SIG Weightless Special Interest Group

WiFi Wireless Fidelity

WirelessHART Wireless Highway Addressable Remote Transducer

WLAN Wireless Local Area Network

WPAN Wireless Personal Area Network

WPT Wireless Power Transfer

WSNs Wireless Sensor Networks

WTRP Wireless Token Ring Protocols

Wu wake-up

WuC WUR Call

WUR Wake-Up Radio

WUR-TICER-MAC WUR Transmitter Initiated Cycled Receiver

WuRx Wake-up Receiver

WuTx Wake-up Transmitter

1

Introduction

The Internet of Things (IoT) ecosystem facilitates the connection and data transfer of a large number of physical things via the Internet. These devices are equipped with unique hardware and software that improves the performance and efficiency of various applications and services (4). As part of the IoT paradigm, these improvements seek to enhance every element of human life and society, from process management in industrial automation to digital hospitals in healthcare services (5).

The idea of the IoT paradigm was first introduced by Kevin Ashton in 1999, who considered Radio Frequency Identification (RFID) as the fundamental technology for IoT systems. He declared that IoT aims to integrate short-range mobile transceivers into numerous devices to enable new inter-thing-human communications. However, Cisco reported that the IoT ecosystem was born between 2008 and 2009 when the number of connected devices was estimated to reach 12.5 billion in 2010 (6). According to the latest report from Cisco, approximately 30 billion connected IoT devices will exist by the end of 2023 (7), which follows by a considerable increase in the Compound Annual Growth Rate (CAGR) from 465 billion dollars in 2019 to 1.5 trillion dollars (8).

As the statistics demonstrate, the number of connected devices continues to grow exponentially, which makes providing sufficient energy to sustain this massive ecosystem a significant challenging issue. Research conducted by "The Shift Project" (9) reveals a concerning trend in the energy consumption of IoT deployments, projecting a CAGR of 4.5% from 2312 TWh in 2015 to 4350 TWh in 2025. These predictions raise concerns about the viability of powering IoT devices with conventional batteries, which have limited lifetimes and require frequent replacements. Such challenges risk IoT system failures and highlight the inefficiency and costliness associated with maintaining and replacing batteries, particularly when IoT devices are located in hard-to-reach or hazardous areas across various sectors such as healthcare, industrial, transportation, and residential. Consequently, disposing of billions of batteries in landfills each year poses significant environmental concerns and diminish resources at a planetary scale, including ecotoxicity and water pollution (10). Moreover, EH technologies play a pivotal role in the ambitious Net Zero 2050 project (11), designed to balance the equilibrium between greenhouse emissions extracted from the atmosphere and those emitted into it. The realization of this goal lies on the widespread integration of EH techniques into IoT devices.

As a result, academia and industry have taken an interest in finding ways to extend the lifespan of IoT devices and conserve energy while maintaining optimal performance. In mitigating these negative impacts, power management techniques have been explored, where sustainability plays a pivotal role in optimization of the energy consumption of the network. Effective techniques that move towards sustainability include energy-efficient methods such as lightweight protocols, scheduling optimization, low-power transceivers, and passive techniques. Passive technologies in wireless communication include techniques that do not require an external energy source to transmit data. These techniques involve the harvesting and utilization of wireless energy without the need to convert it into another form of power generation. Energy Harvesting (EH) techniques are included within this paradigm.

In conjunction with energy-efficient techniques that reduce overall energy consumption in networks, recent innovations in IoT technologies have introduced portable devices with small batteries. This has led to the emergence of EH technologies as a promising and environment-friendly solution to provide sufficient energy for these devices and prolong the lifespan of the network while minimizing the drawbacks associated with conventional batteries. The growing interest from academia and industry has contributed to the expansion of the global EH market, which is projected to increase from 360.6 million dollars in 2020 to 987.09 million dollars by 2028 (12).

1.1 Motivation

Moving towards sustainability in IoT systems can be accomplished through the implementation of EH deployments. Nevertheless, integrating EH within the IoT ecosystem poses a significant challenge due to various factors, including device/harvester form factor, end-user device type, the specific IoT application, power density of the harvester, and the type of wireless communication (13).

To gain insight into how EH technologies can be supported in IoT, there is a need to understand the essential role of each component in the IoT device, which is equipped with an energy harvester. Several components come into play when dealing with a sensor equipped with EH technology. First, the specialized energy harvester collects energy from the environment. An energy storage device is necessary to store this harvested energy. Once the harvesting system is connected to a wireless sensor or actuator, the processing unit manages the data collection process. The key goal is to achieve Energy Neutral Operation (ENO), where the energy supplied by the harvester meets or exceeds the system's energy requirements. At the same time, the system must facilitate wireless communication. This concept is illustrated in Figure 1.1, which is extracted from paper (1).

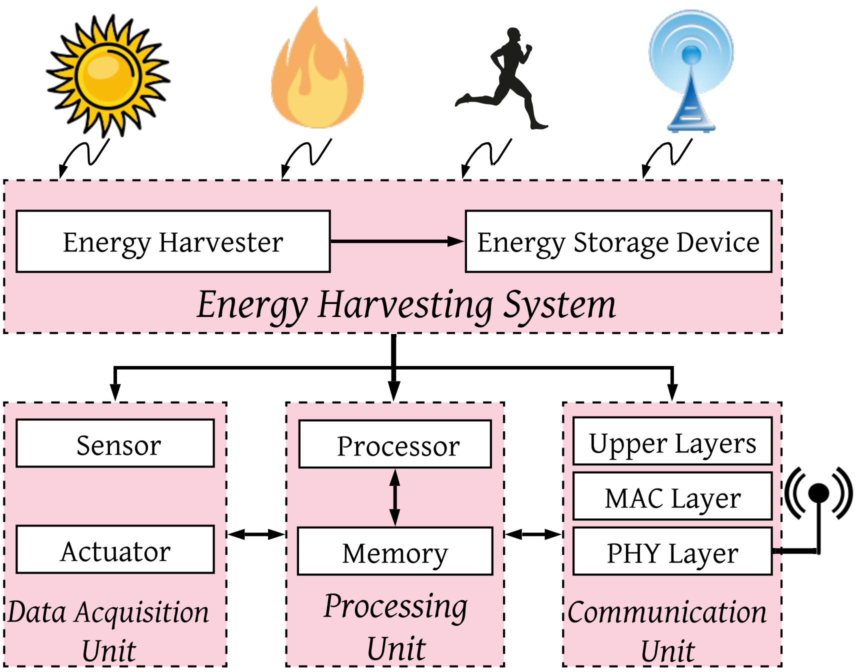


Figure 1.1: General schematic of an IoT node equipped with EH (1).

In the wireless communication field, Key Performance Indicators (KPIs) are known as targeted metrics. They evaluate the performance of various aspects of a wireless network and provide valuable insight into how well the network functions and how effectively it addresses users' needs. IoT applications might be different in their specific KPIs such as data rate, energy consumption, coverage, and latency. For this reason, the IoT industry employs a diverse range of wireless communication technologies to attain specific levels of targeted KPIs for its applications at the communication level. In other words, depending on the deployed wireless communication protocol, each IoT system will have various performance requirements. Thus, selecting a suitable wireless connection technology while installing IoT devices is another critical issue. As shown in Figure 1.2, wireless communication technologies have evolved over time. Since, for many IoT applications, energy consumption is one of the most important KPIs, there is a need for a unified energy model approach to characterize the energy consumption in different IoT wireless communication technologies and understand its impact on IoT performance.

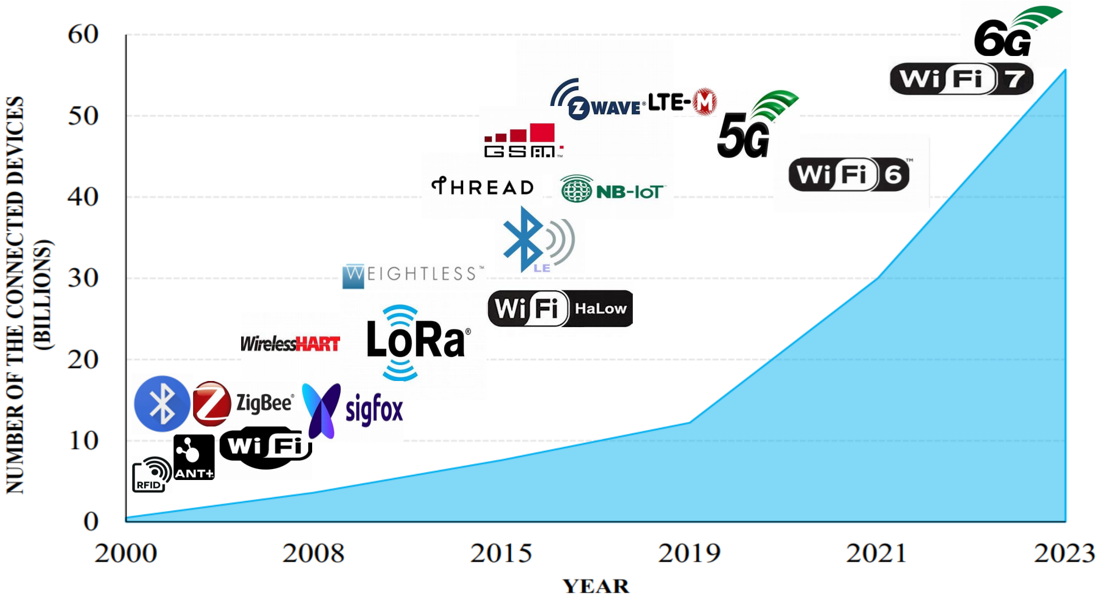


Figure 1.2: Illustration of the Evolution of IoT.

However, achieving sustainability of the IoT systems towards the ENO property, while considering specific factors (such as a small energy harvester size) and meeting the overall system requirements, still presents a gap in the current literature. In addition, the energy provided by EH is not always sufficient for IoT communication technologies because of the limited and intermittent behavior of the energy sources of EH techniques. Hence, the challenge is integrating EH in wireless communication technologies without impacting the performance of the system.

Thus, to successfully integrate EH into IoT systems, optimizing energy consumption in wireless communication technologies across different layers of the IoT architecture is essential. The energy consumption of the IoT protocol stack has been mitigated by using optimization methods such as channel adaptation or energy-aware routing algorithms. However, since the MAC layer, responsible for scheduling data frame transmissions, encounters inherent communication challenges such as collision frames, control packet overhead, idle listening, unused idle slots, and synchronization, it consumes a significant portion of the energy budget in wireless communications. For this reason, the MAC layer operations benefit significantly from optimization algorithms, such as channel access optimization techniques. It is essential to ensure these optimizations and modifications remain compatible with current wireless technologies.

In recent years Machine Learning (ML) algorithms have demonstrated a powerful capability to improve and evolve optimization problems from classical optimization methods in wireless networks. ML-based algorithms might be required to efficiently meet the complex features of different wireless communication technologies, such as Extreme Ultra Reliable Low Latency Communications in cellular networks and Access Point (AP) coordination in Wi-Fi 7 and Beyond.Furthermore, these algorithms can play a crucial role in optimizing the MAC layer to support EH techniques. By leveraging ML, the MAC layer can adaptively adjust parameters based on real-time network conditions and the available harvested energy. This integration of ML and EH, enables intelligent resource management, reducing collisions, improving energy efficiency, and maximizing the benefits of EH in wireless networks. Through efficient resource allocation and intelligent energy management, ML-enhanced MAC layer operations, may aid in enabling a more sustainable approach to wireless communication by minimizing energy waste and prolonging the lifespan of battery-powered devices.

In summary, implementing energy efficient-IoT systems utilizing the latest wireless communication technologies relies on integrating EH techniques. These techniques are essential for ensuring sustainable operation by allowing devices to generate power from their surroundings. In addition, novel and advanced optimization methods need to be integrated to optimize and improve overall efficiency within IoT networks and move towards a more resilient, sustainable, and advanced IoT ecosystem. These optimization methods mainly employ ML techniques, which hold significant promise for enhancing network performance.

1.2 Objectives of the Ph.D.

As emphasized in the Motivation 1.1, achieving sustainability in the IoT ecosystem and integrating EH technologies necessitates a thorough understanding of the energy requirements for communication. Subsequently, employing appropriate optimization methods becomes crucial to enhance system performance, specifically in terms of network energy consumption. This research dissertation aims to introduce and evaluate modifications at the MAC layer of a solar-based Wi-Fi system within a Medical IoT (MIoT) scenario, to mitigate energy consumption while preserving the necessary Quality of Service (QoS) for e-Health applications.

This research dissertation focuses on the following primary objectives that we aim to address:

1.2.1 To review the State of the Art to evaluate the enhancement of IoT performance through the utilization of passive techniques

The rapid development of the IoT ecosystem requires improvement in the performance of the IoT systems, specifically in terms of energy efficiency. Therefore, this evaluation reviews the State of the Art and focuses explicitly on the significance of energy efficiency and the progression towards sustainability within the IoT ecosystem. Thus, the critical aspect is determining the most relevant requirements for an EH method in IoT wireless communication technologies and investigating the possibility of a successful EH integration in the IoT systems through a proper energy model.

1.2.2 To reach an in-depth understanding of MAC layer operations and investigate the impact of these operations on the energy consumption of wireless communication technologies in the IoT ecosystem

The previous objective focuses on the analyzing the energy consumption associated with MAC layer operations in wireless communication. A method to improve energy efficiency at the MAC layer is by integrating EH, however, incorporating EH into the system could increase the initial energy requirements. Hence, minimizing MAC layer operations through optimization methods that address the needs of both EH technologies and IoT systems becomes imperative.

This objective includes a MAC layer protocol, which needs to be compatible with the selected wireless communication and the EH technology. In addition, it is important to note that the rate of harvesting energy has a significant effect on the proposal of the EH MAC protocol.

1.2.3 To enable the EH integration within the IoT scenario through MAC layer optimization

MAC layer optimization methods can effectively reduce energy consumption during operations at this layer. Consequently, it is crucial to identify the optimal values for MAC layer parameters that achieve minimal energy consumption without compromising the performance of other network metrics.

1.2.4 To explore the impact of Reinforcement Learning (RL) optimization algorithms in successfully integrating EH technologies within the IoT systems

The emergence of ML, particularly RL-based optimization, has dramatically enhanced the optimization field, making it more powerful for networking applications. While identifying an optimal configuration for MAC layer parameters can lead to reduced energy consumption in the network, the dynamic nature of network conditions necessitates a flexible approach. Frequent changes in network conditions imply that the optimal value needs to be adaptive and responsive to these fluctuations. RL-based optimization methods are well-suited for this task, as they excel in dynamic environments and can effectively adjust to changing network conditions. Consequently, RL-based optimization methods offer a promising solution to enhance the integration of EH within IoT systems by enabling dynamic and efficient parameter selection.

1.3 Research Methodology

To accomplish the aforementioned objectives, the approach employed in this Ph.D. study can be outlined into two distinct approaches. The initial approach focuses on an exhaustive literature review, developing a cohesive model for assessing energy consumption in wireless communication technologies (Objectives 1.2.1 and 1.2.2). This is achieved by investigating the main databases to find the most relevant articles from indexed journals and conferences, and their corresponding references, cited over the last twenty years. Our search was structured around a selected list of relevant keywords to the topic, ensuring a thorough exploration of the subject matter. The second approach entails designing, implementing, and evaluating a system model to identify optimal MAC layer parameters integrated with EH technology, within QoS-constrained environments, to enhance overall energy efficiency (Objectives 1.2.3). To reach this goal, Network Simulator 3 (ns-3) is selected as the simulation environment, specifically the default WiFi module, which defines several amendments. Among all these amendments, we select the IEEE 802.11n amendment. Then, we implement the AP coordination technique from the upcoming amendment IEEE 802.11bn and demonstrate its backward compatibility. Finally, a similar strategy is adopted to leverage ML technology in optimizing energy utilization within the use case mentioned above (Objectives 1.2.4). In this approach, we utilize ns3-gym, which makes the ML algorithm deployment possible, and we develop RL algorithms for the optimization problem.

The research methodology employed in this Ph.D. study is visually depicted in

Figure 1.3. As illustrated, the initial phase involves a comprehensive exploration of existing challenges and gaps concerning enhancing energy efficiency within IoT systems, aiming to extend the operational lifespan of associated devices. This investigative phase is the momentum for formulating research inquiries aligned with the stated objectives. This work includes problem description, the proposal of potential solutions, and the strategic road map for achieving the objectives. Subsequently, an extensive literature review follows, delving into relevant studies to accumulate foundational insights and identify possible methods for addressing the gaps in this research domain. These studies undergo thorough analysis, finalizing in the constructing of a model tailored to address the defined issue.

In the context of this dissertation, the constraints of IoT technologies are highlighted through an energy model, adjusting with potential IoT technologies and the dynamic characteristics of EH techniques. Aligned with the contextual requirements of the system environment, this model is precisely designed, outlining the selected methodologies and network performance metrics. According to Figure 1.3, the next phase centers on evaluating the proposed model, which is effectively executed through simulations. The chosen simulation platform operates at the packet level, fairly emulating real-world network behaviors and operations. Concluding the methodology, the outcomes of the proposed model are subjected to rigorous validation, substantiated through publication in international journals. This systematic framework repeats consistently across all articulated objectives, ensuring a robust and comprehensive approach to the research work.

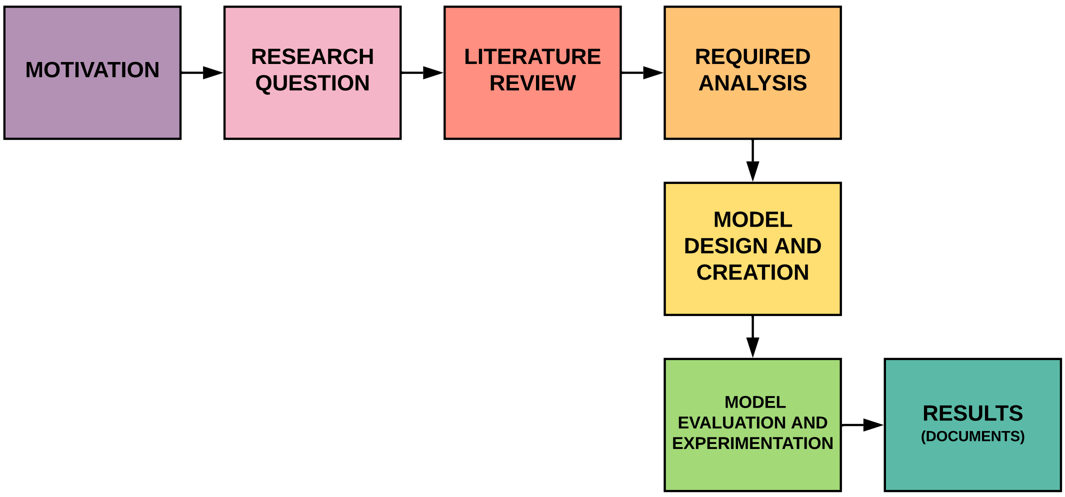


Figure 1.3: Research methodology Steps.

1.4 Contributions of the Ph.D. Dissertation

The main goal of this Ph.D. dissertation is to explore the feasibility of integrating passive technologies, specifically EH, within the IoT ecosystem. Although EH solutions can be beneficial for various IoT systems, their application in MIoT, which accounts for 20% of the global IoT systems (14) offers a dual advantage. Firstly, implementing EH reduces maintenance costs associated with powering medical devices and systems. By harvesting energy from the surrounding environment, IoT devices (including MIoT) can operate without frequent battery replacements or external power sources, leading to cost savings in the long run. Secondly, EH techniques improve human well-being by ensuring reliable and uninterrupted operation of medical devices. Patients and healthcare providers can rely on continuous monitoring and accurate data collection, enhancing patient care and outcomes. Moreover, considering that Wi-Fi is the prevailing wireless communication technology in indoor IoT systems (15), this study investigates the possibility of integrating EH technologies within Wi-Fi technology through extensive simulations. To reach this goal, our first objective is to assess how passive techniques can elevate IoT performance, which requires investigating deeply into MAC layer operations to comprehend their intricacies and evaluate their influence on the energy consumption of wireless communication technologies within the IoT framework. The second objective is to enable the seamless integration of EH within the IoT ecosystem by optimizing the MAC layer. Finally, we explore the efficacy of RL optimization algorithms in incorporating EH technologies into IoT systems to enhance overall efficiency and sustainability.

1.4.1 Analysis of energy considerations and an in-depth exploration into the feasibility of integrating EH within the IoT Paradigm

This contribution (see Chapter 3) encloses an in-depth review of energy-aware MAC protocols, categorizing them based on various dimensions to facilitate the concurrent utilization of EH techniques. In addition, a thorough investigation of wireless communication technologies, evaluating their compatibility with the IoT paradigm and analyzing their MAC layer features and optimization techniques is conducted. By adopting a unified approach, this research contributes to a more profound comprehension of energy models, shedding light on energy requirements of IoT systems and limitations in relation to wireless communication technologies. The functionalities and suitability of existing energy harvesters for IoT wireless communication technologies are also assessed. Furthermore, this contribution comprehensively examines current EH MAC protocols' functionality, benefits, and limitations, specifically focusing on their integration at the MAC layer. Moreover, the energy consumption across different levels of IoT systems, emphasizing MAC layer operations and identifying energy wastage caused by MAC anomalies, is extensively reviewed. Lastly, comprehensive guidelines that address open issues and research challenges on EH MAC protocols within IoT systems are provided.

1.4.2 Energy reduction through MAC layer optimization

This contribution proposes an objective function that, considering medical-grade QoS criteria and energy usage, optimizes a Wi-Fi-based IoT system equipped with EH technology in a field hospital (see Chapter 4). This objective function guides the decision-making process towards achieving the desired QoS while minimizing energy consumption. In addition, a sleep/wake-up mechanism is designed to put specific stations into sleep mode for a specific time interval when their residual energy drops below a particular threshold. This mechanism effectively reduces network energy consumption while maintaining the desired level of QoS for the medical applications. Lastly, extensive simulations within the ns-3 environment are proposed to accurately deploy a Wi-Fi communication for solar-based medical devices. This approach incorporates the AP coordination concept from the upcoming IEEE 802.11bn standard, ensuring backward compatibility with the existing IEEE 802.11 standard.

1.4.3 Dynamic optimization for MAC layer of Wi-Fi

In this contribution, innovative RL-based optimization algorithms are proposed (see Chapter 5), which are specifically designed for a solar-based Wi-Fi system operating in a MIoT scenario. Similar to the previous contribution, this approach ensures the compatibility with the existing IEEE 802.11 standard. To enhance system performance, an objective function is introduced, which aims at maximizing the remaining energy while minimizing both the End-to-End (E2E) delay and Packet Loss Rate (PLR) to fulfill the medical-grade QoS requirements. By introducing RL-based optimization algorithms, our research enhances the previous contribution and improves the flexibility of the algorithm to adapt to the dynamic behavior of dense networks.

1.5 Contributions Alignment with the Ph.D. Dissertation's Research Objectives

In this section, we provide a detailed explanation of the alignment between the designated Research Objectives 1.2 in this Ph.D. study and the specific achievements to effectively address each objective, towards the contributions of this Thesis (c.f. Section 1.4).

After thoroughly investigating the energy demands of wireless communication technologies and their compatibility with IoT systems, we have identified a notable gap in the existing literature concerning the seamless integration of passive technologies within IoT systems. Furthermore, we have recognized a need for insights into how passive technologies, such as EH techniques, can significantly enhance the energy efficiency of IoT systems (c.f. Objective 1.2.1). Since the energy consumption in wireless communication directly depends on the operations at the MAC layer, we have devised a distinctive energy consumption decomposition model focusing on the MAC layer operations. This model is based on an extensive analysis of the operations at the MAC layer, aligning with the requirements of IoT systems and their chosen wireless communication technology (Objective 1.2.2). These two objectives are developed in the Contribution 1.4.1, which is detailed in Chapter 3, and published in (1), where we delve into the comprehensive exploration of these principles.

To accomplish our third Objective 1.2.3, we have conceptualized, executed, and assessed a comprehensive system model. This model allows us to specify optimal MAC layer parameters within QoS-constrained environments, integrating EH technology. This integration, together with wake-up/sleep method deployment, aim to significantly enhance the overall energy efficiency of the network system. This contribution is developed in the Contribution 1.4.2, which is detailed in Chapter 4, and published in (2).

Finally, our fourth and last Objective 1.2.4 is approached by employing a similar strategic approach, leveraging the ML process to optimize energy utilization within a similar use case explained in the previous contribution. This involves designing and implementing a ML algorithm that analyzes real-time data from the IoT system, and fine-tunes MAC layer parameters for energy consumption mitigation and consumption patterns, to achieve an optimal and sustainable operational model. Through iterative learning and adaptation, this ML-driven approach aims to continuously enhance the energy efficiency of the system, making it dynamic to the changes of the environment. Moreover, the addition of ML techniques may increase the likelihood of EH integration within IoT deployments in the future. The accomplishment of this objective is developed in Contribution 1.4.3, included in Chapter 5, and published in our second technical paper (3).

Table 1.1 links the Objectives of this dissertation with the achieved Contributions, in this PhD Thesis in the format of articles compilation.

Table 1.1: Objectives and Contributions alignment within the PhD Thesis.

Objective	Contribution	Chapter	Publication
1.2.1 & 1.2.2	1.4.1	3	(1)
1.2.3	1.4.2	4	(2)
1.2.4	1.4.3	5	(3)

1.6 Overview of the PhD Thesis

The reminder of this PhD Thesis is organized as follows:

Chapter 2 describes the State of the Art of the aforementioned objectives. We conduct an extensive background study on MAC layer protocols, looking into their classifications to grasp their diverse inherent features. Subsequently, we present an in-depth exploration of early and promising wireless communication technologies within the IoT ecosystem. Furthermore, we offer insights into appropriate EH techniques suitable for IoT systems. Following this, we thoroughly examine existing EH MAC layer protocols, analyzing their respective merits and limitations. This research provides valuable insights into the current gap within the literature regarding the integration of EH techniques within the IoT ecosystem. Furthermore, it leads us for offering comprehensive guidelines for future research efforts. Moreover, we justify our choice of the ns-3 simulation environment, highlighting its suitability over other simulators in the networking field, where we emphasize the capabilities that make it a prime choice for our research.

Since this Ph.D. dissertation is prepared based on the papers that have been published (papers compilation), they are explained in three separate chapters, where each chapter contains one of the papers. A brief explanation of the content of each paper is provided as follows.

Chapter 3 offers a thorough and systematic classification of existing EH MAC protocols found in the literature based on the adopted channel access method. This classification highlights the advantages and disadvantages of both traditional and recent innovative approaches. Furthermore, the paper comprehensively examines the energy requirements for the possible wireless communication technologies. It accomplishes this by detailing the actual energy consumption of current wireless communication technologies, which is introduced through a unified approach based on MAC layer protocols. Then, the compatibility of selected EH MAC protocols with potential wireless communication technologies is evaluated in this paper. Lastly, the contribution delves into a detailed exploration of available ambient and non-ambient energy harvesters, assessing their suitability for integration with the current wireless communication technologies.

In Chapter 4 the focus is on the incorporation of EH technologies into a dense Wi-Fi network. The paper introduces an optimization algorithm in the MAC layer motivated by the AP coordination method discussed in the upcoming IEEE 802.11be amendment (16). This algorithm aims to find the optimal Contention Window (CW) combination separately in the master and slave cells. Its objective is to meet the QoS requirements in a restricted QoS environment while minimizing the energy consumption of the network. Moreover, a sleep/wake-up method is proposed, which significantly reduces energy usage within the network. The effectiveness of the proposed algorithm is assessed through extensive simulations conducted in a dense Wi-Fi network scenario, specifically in a field hospital where all devices are equipped with solar cells.

Chapter 5 focuses on introducing RL-based optimization algorithms in the MAC layer of a dense Wi-Fi network powered by solar energy. The primary objective of this paper is to explore the feasibility of integrating EH technologies while ensuring the provision of QoS for medical applications. By incorporating RL-based optimization algorithms, this paper builds upon previous work, which is presented in Chapter 4, and enhances the flexibility of the algorithm to adapt to the dynamic nature of dense networks. These RL-based algorithms aim to reduce the energy consumption associated with MAC layer operations in a solar-based Wi-Fi network. Additionally, they endeavor to meet specific QoS parameters which are essential for medical applications, such as PLR and E2E delay, thus improving the overall performance of the network in medical-grade scenarios.

Finally, Chapter 6 summarizes the findings of this Ph.D. thesis. We elaborate on the outcomes and concluded remarks of each paper and explain how the contributions are connected. By outlining the potential and future research directions, the chapter aims to inspire and guide future researchers in expanding upon the existing knowledge and addressing the unresolved questions or challenges in the domain.

It is essential to emphasize that the provided bibliography included in this dissertation, only includes references explicitly cited in Chapters 1, 2, and 6. Readers keen on exploring the referenced papers can find them in their respective chapters.

2

State of the Art

In wireless communication, the optimization of the MAC layer operations significantly affect the energy efficiency of IoT devices. A MAC classification helps to comprehend the features of various MAC techniques and their limits in the IoT environment. Given that a variety of wireless technologies are already used at the communication level of IoT systems, a general overview of each technology, and its MAC layer activities, must be carried out to understand each technology's energy requirements. As mentioned in the Introduction 1, since integrating EH technologies is a promising solution to keep powering the IoT devices up, it is necessary to estimate the amount of energy each harvester contributes to the system. Furthermore, mitigating the energy consumption of the system may also increase EH integration within IoT deployments in the future. Hence, designing and implementing an ML algorithm that analyzes real-time data from the IoT system and fine-tunes MAC layer parameters, may contribute towards these goals. For this reason, an introduction to ML algorithms which are relevant to this PhD Thesis is also included in this State of the Art. Finally, the methodological approach used in this Thesis requires the precise simulation of wireless communication scenarios. To support the distinction and suitability of the selected simulation environment for this Thesis (ns-3), in this State of the Art we included a comparison of the advantages and disadvantages of this simulator over other simulators in the networking field.

This chapter is organized as follows: Section 2.1 presents the main categories of the energy-aware MAC protocols for IoT systems. Next, in Section 2.2, the early wireless communication technologies, and then in Section 2.3, potential wireless communication technologies for IoT systems are explained. Section 2.4 summarize the relevant energy harvesters for IoT systems. A comprehensive comparison between wireless network simulators, the suitability of ns-3 as the evaluation tool used in this dissertation, and its layered architecture is presented in Section 2.5. In Section 2.6, an introduction to ML methods relevant to the goals of this Thesis are presented. Finally, Section 2.7, summarizes the State of the Art most relevant points.

2.1 Categorization of Energy-Aware MAC Protocols for IoT Systems

In line with the IoT protocol stack, the MAC layer functions as a sub-layer within the data link layer. Its primary role involves orchestrating the transmission schedule and potential re-transmissions across the shared medium. In wireless communication technologies within IoT systems, the MAC layer's operations, which facilitate adaptive channel access, encounter challenges such as collisions and idle listening (especially in random access) or issues like synchronization and unused idle slots (in scheduled access). Consequently, these challenges significantly consume the energy resources available to IoT systems.

Notably, while deploying EH technologies can extend battery life, the unpredictable and unstable nature of the obtained energy poses compatibility issues with conventional MAC layer mechanisms. Hence, modifications are essential to integrate these technologies effectively. Given that one of the primary objectives of this Thesis is to enable EH within the MAC layer of IoT systems, to move towards sustainability in IoT systems, a comprehensive understanding of each MAC protocol's functioning is critical. Additionally, exploring the inherent limitations in existing MAC protocols becomes crucial. This exploration can be facilitated through an in-depth categorization of energy-aware MAC protocols, taking into account their performance and distinctive features.

The following section categorizes channel access techniques into four main categories, and provides a brief explanation of each one. Then, Chapter 3 will explain techniques within each category in detail, where the categorization will be clarified through an illustrative approach.

1. Random Access: Within this category, a coordinator is absent to control transmissions, with each node initiating transmission independently at any given time. This category is divided into two subcategories: carrier sensing and blind access. The decentralized nature of methods in this category offers advantages like immediate transmission, yet their disposition for collisions presents a significant challenge, leading to higher energy consumption.

   To delve deeper into the complexity of the random access category outlined in this subsection, interested readers are directed to references such as (17, 18, 19) for more comprehensive details.

2. Scheduled Access: In the scheduled access category, frame transmissions

follow an organized structure, with all nodes initiating transmissions at predetermined slots (Fixed Assignment) or under the guidance of a coordinator (Dynamic Assignment). Compared to the random access category, this organized approach mitigates energy wastage associated with idle listening and collisions, making it more energy-efficient.

However, this efficiency comes at the cost of reduced flexibility for individual nodes, as the coordinator node controls them. Parameters such as Quality of Service (QoS) and Quality of Experience (QoE) may need to be more adaptable. Additionally, the coordinator node's role in making numerous decisions increases operational complexity, compared to other nodes in the network. For a more in-depth understanding of the scheduled access category discussed in this subsection, readers are encouraged to explore references such as (17, 20).

3. Hybrid Access: This classification integrates the advantages of random access (characterized by a distributed nature and full channel utilization) and scheduled access (offering contention-free operation for long frames), mitigating their drawbacks. Within this category, three subcategories exist: random access, scheduled access combinations, and duty-cycled access operations. To gain a deeper comprehension of the hybrid access category highlighted in this subsection, readers are motivated to delve into resources such as (21, 22, 23).

4. Cross-Layer: Enhancing the management of network peripherals is achievable by comprehending the dynamics of individual layers within the IoT protocol stack. Within this category, the simultaneous interaction of two or three layers of the IoT protocol stack is employed to optimize the network's performance, focusing on minimizing energy consumption. For further information, regarding this category the readers can consult the following survey papers (24, 25).

2.2 Early Wireless Communication Technologies Towards IoT Paradigm

Although IoT devices can be connected to the Internet through wired or wireless connections, wireless communication technologies are considered an essential part of IoT systems. However, there exist wireless technologies which were introduced before the advent of the IoT paradigm. Thus they did not consider IoT requirements in their protocol design. These technologies are essential because they are, in a way, the foundation of other technologies that meet IoT requirements. In this section, a brief description of these wireless technologies is given.

2.2.1 General Packet Radio Service (GPRS)

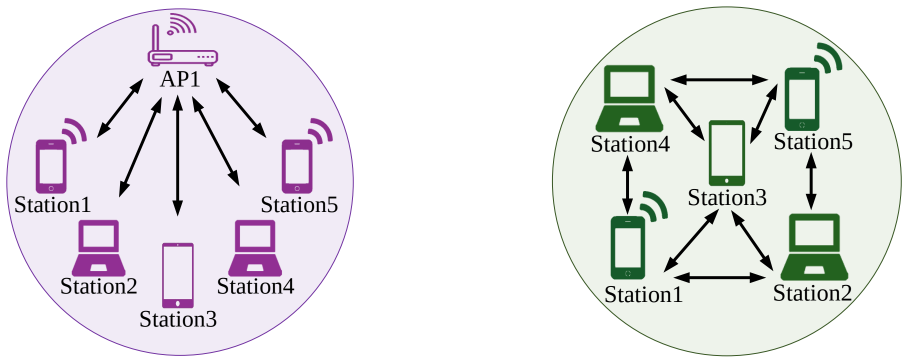
GPRS is a packet-oriented communication standard that was introduced in 2000-2001. Since this technology is between the second generation (2G) and the third generation (3G) of cellular communication, it is known as 2.5G. GPRS is able to provide moderate data rates (56-114kbit/sec) and deploy TDMA for channel access in the Global System for Mobile communication (GSM) systems (26). It supports smart devices by enabling internet applications via Wireless Application Protocol (WAP). GPRS defines three types of devices, class A devices that support GPRS and GSM services at the same time. The second type, known as class B, can make a connection between GPRS and GSM services but not at the same time. The last type, class C, relates to devices that are able to support GPRS or GSM services by switching between them manually. The network connection supports point-to-point or point-to-multipoint communications. GPRS is a widely adopted solution for IoT due to existing development in large range sub-GHz band and efficient transfer of short messages.

2.2.2 Wireless Local Area Network (WLAN)

Among different wireless communication technologies, Wi-Fi is widely used in IoT and has evolved over time. The Institute of Electrical and Electronics Engineers (IEEE) 802.11 technology was designed based on a random access mechanism (CSMA/CA), which is an energy consuming protocol (27). The reason for such energy consumption is the collision avoidance functionality of this protocol, which keeps stations awake (in active mode) to listen to the channel for a certain duration before attempting to transmit (28). Next, the early versions of the 802.11 technology are briefly described.

1. **IEEE 802.11 legacy (29)**:

    (a) Architecture: The architecture of the IEEE 802.11 protocol includes two types of networks, infrastructure and ad hoc networks. In the infrastructure networks, all the stations are communicated through the APs, whereas in the ad hoc networks, stations communicate with each other directly and without requiring a centralized entity. Infrastructure networks are more suitable for permanent networks and, compared to ad hoc networks, need less network resources, are easy to scale up, and have less interference. A simple illustration of the infrastructure and the ad hoc networks are shown in Figure 2.1.



(a) Infrastructure-based WiFi network

(b) Ad hoc-based WiFi network

Figure 2.1: General architecture of the WiFi networks.

(b) Fundamental mechanism of MAC protocol: The fundamental technique of the MAC layer in IEEE 802.11 standard is a two way handshake protocol, known as the Distributed Coordination Function (DCF). It uses a Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) method with binary exponential back-off. Figure 2.2 depicts the default access technique known as a two-way handshaking scheme. According to CSMA/CA mechanism, stations monitor the channel before sending the data frame. They will start a back-off countdown if they sense the channel idle for a specific time interval known as Distributed Inter-Frame Space (DIFS). Otherwise, if the channel is sensed as busy, the stations keep monitoring the channel until the channel is sensed idle for a DIFS. Then, the back-off countdown timer starts after the channel is sensed idle for a DIFS. Since DCF is defined in a discrete-time back-off manner, each transmission must begin at the start of the time slot. Moreover, stations wake up and ask the AP for buffered frames using the Power Save Poll (PS-Poll) control frame. The PS-Poll control frame was considered the power management method in the standardized amendments until 2005.

(c) MAC protocol anomalies: The MAC layer of the IEEE 802.11 includes inherent characteristics that each cause an increment in the energy consumption of the network. These anomalies are collision frame, transmission overhead, overhearing, hidden and exposed terminal.

Within Random-based access mechanisms, a **collision frame** emerges when two or more stations simultaneously attempt to transmit data frames over the shared channel. This collision results in the discarding

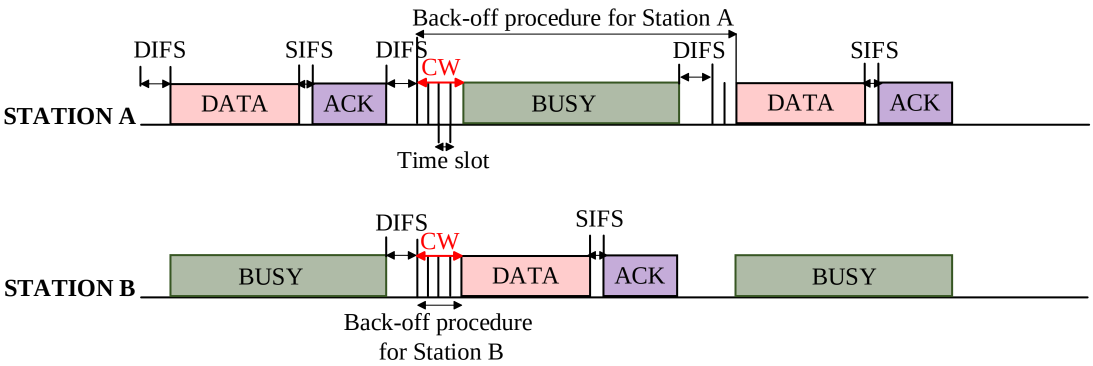


Figure 2.2: CSMA/CA Back-off procedure (2).

of data frames and requires a re-transmission.

The DCF mechanism suffers from different sources of **transmission overhead**. The first source of overhead is the interference of non-Wi-Fi and Wi-Fi devices. The second reason is the random back-off procedure, where the lengthy back-off procedure increases the transmission overhead. The third source of extra transmission overhead is the control frames that, although they do not contain data, are necessary for communication management.

Wi-Fi stations receive data frames that are not meant for them, which means they receive any wireless interference within their communication range. This phenomena is known as **overhearing** and it intensifies in the case of a dense network.

In random-based access mechanisms, if two stations that are out of the communication range of each other start transmission simultaneously to a receiver, the receiver may face a collision, and the two senders are known as **hidden terminals**.

A station in random-based access mechanisms may be prevented from starting the transmission and faces unnecessary waiting due to ongoing transmissions of neighboring stations. This anomaly is known as **exposed terminal**.

(d) Enhanced Distributed Channel Access (EDCA): The IEEE 802.11 standard group defines another mechanism known as EDCA, which supports differentiated Quality of Service (QoS) in Wi-Fi communications. This mechanism introduces four different Access Categories (AC_{VO}, AC_{VI}, AC_{BE}, and AC_{BK}) to prioritize channel access, where the AC_{VO} has the highest priority and AC_{BK} has the lowest priority. The AC_{VO}, AC_{VI}, AC_{BE}, and AC_{BK} categories are meant for voice, video, best-effort, and background traffic respectively. According to this mechanism, the MAC layer parameters such as CW_{min} and CW_{max}, Arbitrary Inter-Frame Space (AIFS), Transmission Opportunity (TXOP), and queue length are set to different values to achieve this prioritization. For instance, AC_{VO} parameters are assigned to the smallest values among other categories to give the highest transmission opportunity to the traffic under this category. However, since different applications require various ACs, and Wi-Fi proposed fixed EDCA parameters for each AC (Table 2.1), it is unsuitable and unfeasible for heterogeneous networks (30), such as e-Health networks, where the time-sensitive and emergency traffic require a certain level of QoS. For this reason, new ACs with special queues are required. Moreover, as explained in (31), since the CW is the principal parameter of the back-off procedure, among the EDCA-related parameters, which are listed in Table 2.1, CW has the most impact on rescheduling the transmissions and QoS parameters.

Table 2.1: Default EDCA ACs parameters (2).

Access Category	$\mathbf{CW_{min}}$	$\mathbf{CW_{max}}$	**AIFSN**	**TXOP**
VO	7	15	2	1.5 ms
VI	15	31	2	3.0 ms
BE	31	1023	3	0.0 ms
BK	31	1023	7	0.0 ms

As highlighted in previous works (32, 33, 34), since the inherent behavior of DCF and EDCA mechanisms are contention-based, collisions may be caused by simultaneous transmissions, which is one of the reasons that imposes extra energy consumption on the Wi-Fi stations. It is worth mentioning that, in Time Division Multiple Access (TDMA), a control channel makes the channel collision-free; however, this feature is not available on Wi-Fi. The other reason behind the energy-hungry feature of the DCF mechanism is the transmission errors due to the imperfect channel condition, which causes re-transmission. Besides the amount of energy consumed in the transmission state, the idle state of DCF can also consume a significant amount of energy. Although various methods have been introduced to reduce these effects, they need to precisely select the involved parameters to avoid extra energy consumption (35). For instance, setting the beacon and idle intervals in the power-saving mode is very important to prevent frequent wake-up nodes, or simultaneous wake-ups, from wasting the energy of station.

(e) **Four-way handshake mechanism**: The DCF method can be advanced by sending special short Request To Send (RTS) and Clear To Send (CTS) frames before the actual frame transmission to reduce the collision probability due to the hidden terminal anomalies. As shown in Figure 2.3, before the frame transmission is triggered, the RTS frame is sent, and only if the CTS frame is successfully exchanged, then the channel can be reserved for the period needed to transport the data frame. This approach is an optional mechanism that increases the overhead in the case of small data frames while enabling other stations to know the actual transmission length before the long data frame is delivered.

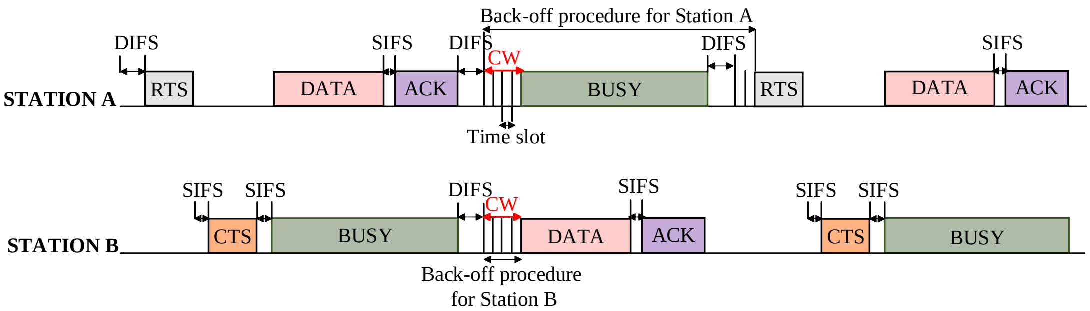


Figure 2.3: A simple illustration of the four-way handshake mechanism.

2. **IEEE 802.11a\b\g (36)**:

   The first group of IEEE 802.11 amendments was introduced, between 1999 and 2003, as IEEE 802.11a\b\g. IEEE 802.11a works at the 5GHz band, whereas IEEE 802.11b\g work at the 2.4GHz frequency band. Working at a 5GHz frequency band reduces the probability of interference for IEEE 802.11a signals. Compared to IEEE 802.11b\g, IEEE 802.11a suffers from low range commutation due to its small wavelength and vulnerability to signal absorption by physical objects. It is worth mentioning that all these amendments apply power management that uses PS-Poll control frames. In this mechanism, the station has to transmit a PS-Poll control frame to ask the AP to allocate a buffered uni-cast frame.

3. **IEEE 802.11n (37)**:

   IEEE 802.11n was followed by IEEE 802.11a\b\g and was standardized in 2009. It is the first wireless network standard that enables MIMO transmissions and, thus, enhances the standard for high throughput communications, while also supporting both 2.4GHz ad 5GHz frequency bands (5GHz is optional). Similar to the IEEE 802.11g amendment, this amendment is backward compatible with legacy and Previous ones (IEEE 802.11a\b\g amendment). In this amendment Spatial Multiplexing Power Saving (SM-PS) and multi poll power saving methods are used to reduce the power consumption of the operations. In the SM-PS method all radios but one will be turned off by a device. This significantly lowers the possible data rates. After that, the station stops supporting MIMO and many of the benefits of IEEE 802.11n. The second method, is able to reduce the power consumption by scheduling the uplink and downlink transmissions through the power saving multi poll frames.

4. **IEEE 802.11s (36)**:

   The IEEE 802.11s amendment was mainly designed for wireless mesh networking by introducing a mandatory default routing protocol – Hybrid Wireless Mesh Protocol (HWMP). The physical layer of this amendment is designed based on IEEE 802.11n and its MAC layer is based on the IEEE 802.11n and IEEE 802.11e amendments. According to this amendment, the WiFi devices are a Mesh Point Portal (MPP) which provides a gateway to the wired network, Mesh Point (MP), which provides a wireless backbone between other meshed devices and Mesh AP (MAP) that provides a wireless backbone as well as serves client stations. Moreover, this amendment introduces a power-saving mechanism known as the Peer Service Period (PSP). In this approach, if the receiver is operating in PSM, which means it is operating in light sleep or deep sleep mode for the connection, then a predetermined continuous period is employed to exchange buffered frames in the link.

5. **IEEE 802.11ac (38)**:

   The following amendment was IEEE 802.11ac, introduced in 2013 and built on top of IEEE 802.11n. It supports simultaneous connections in 2.4 and 5 GHz bands and provides backward compatibility with IEEE 802.11a\b\g. Since these amendments do not meet IoT communication requirements, (e.g. dense network deployment and low power communications) other amendments and communication technologies have been introduced to support IoT systems. Based on the VHT TXOP power saving method, a station will turn off its radio during a transmission if it notices that another station has a TXOP. The more battery is conserved, the longer the TXOP and the longer the sleep period.

2.3 Overview of Potential Wireless Communication Technologies for IoT

IoT low-power technologies and approaches have recently received increased attention. In this area, new concepts have been brought to satisfy IoT requirements. This section introduces WLAN amendments that can be deployed in IoT systems, together with their MAC layers characteristics, and lists the other potential wireless communication technologies for IoT systems. Furthermore, in Chapter 3, these possible wireless communication technologies will be explained in detail and aligned with their energy models.

2.3.1 WLAN

The IEEE 802.11 standard group has introduced in recent years different amendments that aim to satisfy the IoT systems requirements. Within this amendments, the original channel access method has been changing through the technical definition of each amendment, looking for better performance in IoT systems.

1. **IEEE 802.11ah**:

   In 2017 the IEEE 802.11 Working Group published the IEEE 802.11ah amendment (39) for supporting the concept of IoT. The physical layer of this amendment is a modification of the physical layer of IEEE 802.11ac, providing sub-1GHz bandwidth (863-868 MHz in Europe, 755-787 MHz in China and 902-928 MHz in the USA) (40) and a new Modulation and Coding Scheme (MCS), to reduce interference and extend the coverage range up to 1.5km (41). Similar to the IEEE 802.11 legacy, the channel access method of IEEE 802.11ah is based on CSMA/CA. However, some additional features of the MAC layer such as hierarchical Association IDentifiers (AID), group sectorization, and Restricted Access Window (RAW), make IEEE 802.11ah acceptable for a large number of devices deployment, by reducing the contention in the medium. Among these features, RAW is considered an optional one. Moreover, this amendment meets IoT requirements in terms of low power consumption by introducing new MAC features such as Relay Access Point (Relay AP), bi-directional Transmission Opportunity (TXOP), Target Wake Time (TWT) and the optional feature RAW. The first feature increases the connectivity range of the APs and the duration of inactive mode of a node, the second feature reduces the awake time of the stations and the last one reduces the signalling overhead (41).

2. **IEEE 802.11ax**:

The Task Group 802.11ax (TGax) started the IEEE 802.11ax project in 2014 (42). Contrary to the IEEE 802.11ah, which has been designed to meet IoT requirements, the IEEE 802.11ax amendment was designed for dense deployments. The physical layer of this technology is a modification of the IEEE 802.11ac amendment, operating in 1-6GHz frequency bands. The channel access method of this technology adds OFDMA on top of CSMA/CA, which is able to support MU. The most relevant modification regarding energy efficiency is introducing a MU-Multiple Input, Multiple Output (MU-MIMO) uplink communication, where a control frame with scheduling information is used, making this technology appropriate for dense deployments. A MAC feature that makes IEEE 802.11ax a suitable technology for dense environments is the Basic Service Set (BBS) coloring, where the information of neighbors increases the TXOP of the station, and in consequence increases the spatial reuse (43). Moreover, in this technology energy efficiency can also be achieved through microsleep, TWT, and Opportunistic Power Save (OPS) approaches (42). Microsleep mechanism is the extended approach defined in IEEE 802.11ac, which keeps the stations in deep sleep mode during an uplink or TXOP transmission within the same BBS. TWT was adopted from IEEE 802.11ah, where the stations wake up only for TWT Service Period (SP), and it does not depend on other control frame modifications. The OPS is a combination of Traffic Indication Map (TIM) segmentation and TWT SPs, where only a group of stations awake for data transmissions and other stations stay in sleep mode (42).

3. **IEEE 802.11ba**:

   Unlike the above IEEE 802.11 amendments, the IEEE 802.11ba is designed for green IoT applications, and aims to balance the trade-off between low latency and low power states in devices (44). The aim of this technology is to reduce the power consumption of the active mode to less than 1mW (45). The IEEE 802.11ba TG started to work on WUR in 2017 (46) and at the moment of writing this dissertation, the standardization of IEEE 802.11ba is under development. The implementation of the WUR system is based on a Wake-up Transmitter (WuTx) and Wake-up Receiver (WuRx). On the receiver side, there are two transceivers, which are known as primary and WuRx radios. In this technology, primary radio is usually off and only wakes up to receive an incoming transmission, and the WuRx is responsible for receiving a 1bit On-Off Keying (OOK) signal known as WUR call (WuC) from other devices (47). Since the WuRx is a very low power consumption radio and the primary radio wakes up on-demand, the trade-off between low latency and low power communications can be balanced (48). Since one of the requirements of this technology is the compatibility with 802.11

legacy, the frequency band in IEEE 802.11ba for WuTx is 2.4GHz (47). The channel access method of WuR is Enhanced Distributed Channel Access (EDCA) based on CSMA/CA.

4. **IEEE 802.11be**:

   Along with the aforementioned IEEE 802.11 amendments, an upcoming IEEE 802.11be or Extremely High Throughput (EHT) has features that IoT systems can benefit from them (started in May 2019). The IEEE 802.11be is built on top of the IEEE 802.11ax amendment and will support real-time applications, where QoS provisioning is challenging. In addition, this amendment will provide a very high data rate and makes massive Multi-Input Multi-Output (MIMO) communications possible. Some advanced modifications and enhancements are introduced at the Physical (PHY) and MAC layers to fulfill these features. For instance, the AP coordination and Hybrid Automatic Repeat Request (HARQ) are presented at the MAC layer. According to the AP coordination technique, so-called master APs, to improve the performance of their associated non-AP stations, have the ability to communicate with other APs located within its transmission range (slave APs), where the master AP receives the beacon frames from the slave APs. In this technique, the master AP is able to dynamically request the slave APs to reschedule the resources based on the channel conditions (cf. Figure 2.4) (49). It is worth mentioning that this technique is specifically designed for the needs of uncoordinated systems; however, the coordinated systems can benefit from the concept of this technique. Moreover, the HARQ technique combines the forward error correction method and ARQ to deliver reliability for data frame transmission. Furthermore, the pick rate, channelization, and time planning at the PHY layer are improved (16, 50). The amendment has currently reached a mature stage with the release of multiple drafts and the definition of a set of features. The 802.11be TG is expected to produce the final amendment in May 2024.

5. **IEEE 802.11bn**: This Study Group (SG) was established in July 2022 to provide specific support for Ultra-Reliable Low-Latency Communication (URLLC). The Ultra High Reliability (UHR) SG will develop a fresh project outlining the particular goals, frequency bands, and technologies to be explored beyond the scope of 802.11be. The plan is to constitute the UHR TG by November 2023, following the traditional single-release standardization cycle, scheduled to conclude in 2028. This initiative will define the protocol functionalities for future Wi-Fi 8 products, emphasizing areas where improvements compared to 802.11be, such as Data rates, latency, and jitter, while considering mobility and overlapping BSSs (OBSSs). Reuse of the

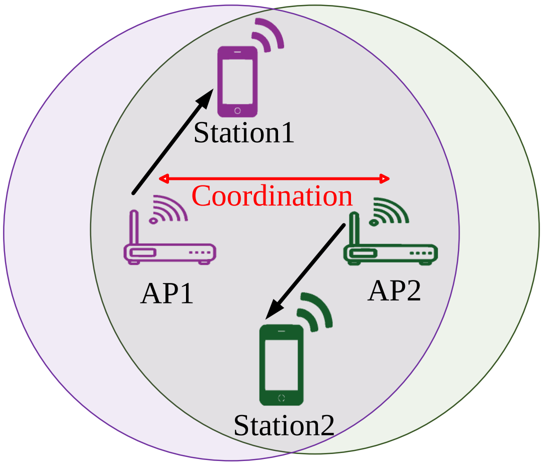


Figure 2.4: AP coordination concept (2).

wireless medium. Power saving and integration of AI/ML methods in this amendment.

Table 2.2 summarizes the continuous evolution of IEEE 802.11 standards over time.

Several technologies fall within the category of potential communication technologies for IoT systems, specifically under the categories of Low Power Area Network (LPWAN) such as LoRa, Sigfox, and NB-IoT; Radio Frequency Identification (RFID) encompassing both passive and active techniques; and Wireless Personal Area Network (WPAN) technologies like BLE and Zigbee. As mentioned earlier these technologies will be explained in detail in Chapter 3. Other potential communication technologies can be listed as Z-Wave, Weightless SIG, Wireless Highway Addressable Remote Transducer (WirelessHART), THREAD, ANT+, Long Term Evolution for Machines (LTE-M), and Extended Coverage Global System for Mobile communication (EC-GSM). Readers interested in further details of different LPWAN technologies are referred to the papers (51, 52).

2.4 Energy Harvesting Solutions for IoT Technologies

EH systems play a crucial role in the IoT paradigm, contributing to extending battery lifetimes, enhancing energy efficiency, and establishing sustainable IoT systems. The classification of EH mechanisms relies on intrinsic characteristics such as scalability, maintainability, capacity, form factor, and sustainability, focusing on improving the lifespan of IoT devices.

Table 2.2: Consistent development of IEEE 802.11 over Time.

Wi-Fi Generation	Amendment	Objective	Power management method	Data rate	Frequency	Range	QoS	Year	Status
Wi-Fi 0	IEEE 802.11 legacy	PHY and MAC layers specifications	PS-Poll control frame	1-2Mbps	2.4GHz	<100m	✗	1999	Standardized
Wi-Fi 1	IEEE 802.11b	Higher Speed PHY extension in the 2.4GHz	PS-Poll control frame	1-11Mbps	2.4GHz	<140m	✗	1999	Standardized
Wi-Fi 2	IEEE 802.11a	High Speed PHY in the 5 GHz	PS-Poll control frame	6-54Mbps	5GHz	<120m	✗	1999	Standardized
Wi-Fi 3	IEEE 802.11g	Further Higher Data Rate Extension in the 2.4 GHz	PS-Poll control frame	6-54Mbps	2.4GHz	<140m	✗	2003	Standardized
Wi-Fi 4	IEEE 802.11n	Enhancements for HT	Spatial Multiplexing Power Save/Multi-Poll	72-600Mbps	2.4 5GHz	<250m	✓	2009	Standardized
–	IEEE 802.11s	Mesh Networking	Peer Service Period	72-600Mbps	2.4 5GHz	<250m	✓	2011	Standardized
Wi-Fi 5	IEEE 802.11ac	Enhancements for VHT for Operation below 6 GHz	VHT TXOP Power Save	1.3-2.3Gbps	5GHz	<100m	✓	2013	Standardized
Wi-Fi 6	IEEE 802.11ah	Sub 1 GHz unlicensed Operation	Restricted Access Window	347 Mbps	Sub-1GHz	<1.5km	✓	2016	Standardized
Wi-Fi 6	IEEE 802.11ax	Enhancements for HE WLAN	Opportunistic Power Save Microsleep	9.607 Gbps	1-6GHz	<300m	✓	2021	Standardized
–	IEEE 802.11ba	Extremely low power consumption	Wake-up Radio operation	0.25Mbps	2.4 5GHz	<50m	✓	2021	Standardized
Wi-Fi 7	IEEE 802.11be	EHT	Independent channel access and power states	40Gbps	1-7GHz	30-120 m	✓	2024	Active
Wi-Fi 8	IEEE 802.11bn	UHR	Distributed Multi link operation and restricted TWT	100Gbp	1-7.250 GHz		✓	2028	Active

According to the energy source, EH technologies are divided into two main categories: ambient environment and external sources. In the first group, energy harvesters extract energy from various sources including light (such as sunlight or artificial light), heat (thermal sources), and fluid flow (such as wind or hydro power). In the second group, energy can be harvested from the human body, utilizing parameters such as heart rate, body temperature, respiration, and mechanical movements of joints like the ankle or elbow. Additionally, energy can be harnessed from physical activities such as walking, running, or cycling. Mechanical energy harvesters extend beyond human activities to capture energy from any mechanical motion, such as driving. However, Wireless Energy Harvesting methods (WEH) offer further possibilities. In this approach, energy can be scavenged either from the surrounding environment or from an external source providing waves for RF (Radio Frequency) harvesters. When energy is obtained from the environment, WEH falls into the first group, whereas if it relies on an external source, it falls into the second group as an additional power source.

This categorization is depicted in Figure 2.5. Chapter 3 delves into a comprehensive exploration of the most relevant IoT-related features, structures, and functionalities of these EH technologies.

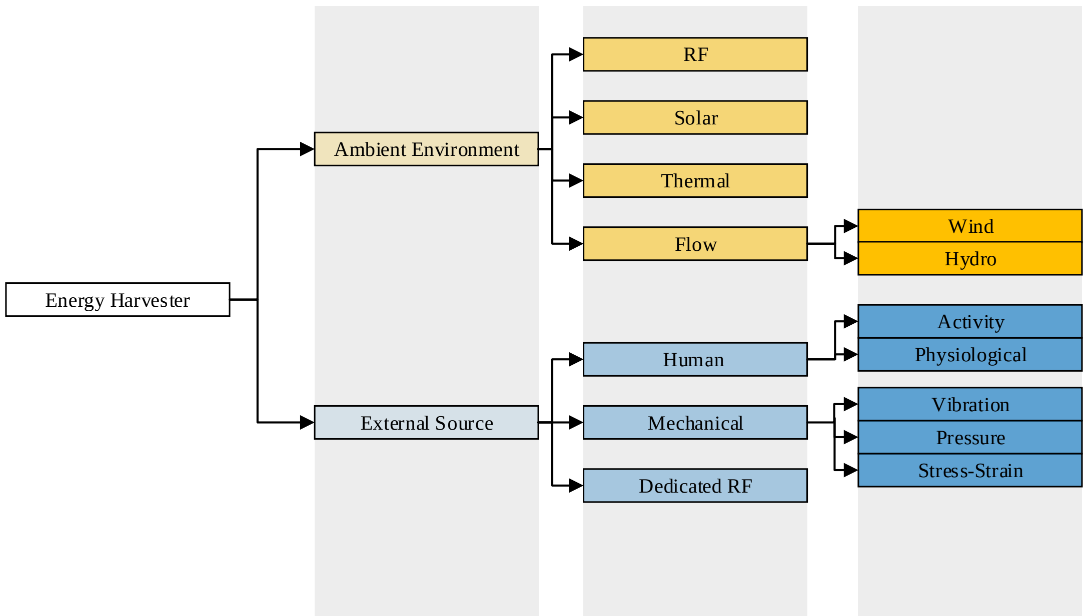


Figure 2.5: Energy harvesters categorization.

2.5 Network Simulators

According to the available literature in the wireless network community, researchers have been extensively conducting simulations to evaluate the performance of different modifications and protocols proposed at different levels of the wireless networks in various simulation tools. Some of the current network simulators are listed as follows, Network Simulator 2 (ns-2) (53, 54), QualNet (55), Cooja (56), GloMoSim (57), Objective Modular Network Testbed in C++ (OMNET++) (58), Optimized Network Engineering Tools in C++ (OPNET++) (59), J-Sim (60), NetSim (61, 62), and Simulink MATrix LABoratory (MATLAB) (63).

According to the objectives of this Thesis, the selected simulator needs to be capable of real-world code integration and fast code execution for Wi-Fi-based IoT systems (dense scenarios). In addition, the simulator has to support and provide accurate models for energy and energy harvesting analysis. Moreover, the contribution to the core code of the simulator needs to be applicable. The essential indicators among the network simulators mentioned above are highlighted in Table 2.3. As shown among these network simulators, ns-3 is an open-source simulator, which provides many features that need to be accomplished to meet the IoT requirements. Some of these features include the high-performance core that enables parallelization, supporting high-fidelity models of cellular networks and Wi-Fi with scalability and robustness. Fundamentally, ns-3 is built on ns-2 and improved it in different aspects such as implementation code, execution environment (ns-3 enables running Linux kernel code and real applications through Direct Code Execution) and low level of abstraction by allowing researchers to identify and reassign the parameters as new configurations as desired. Additionally, ns-3 introduces optional Python bindings, makes the core code development more manageable, and makes the interconnection modules possible (new software core and modular integration). Moreover, the modular representation of network devices and sockets is near to realism, and the testbed integration (packet sending over real NICs for testbeds) is possible based on the needs of the researchers. Thus, particularly in the case of simulating IoT systems with unpredictable and dynamic network behavior, the researchers can benefit from the analysis obtained from real-world scenarios. Furthermore, it makes the analysis more accessible by introducing the virtualization and tracing the statistics of the network, which provide essential information for the analysis (64). Thus, ns-3 outperforms other network simulators, and these features have led us to choose ns-3 to analyze our research lines and proposed scenario. An overall comparison between network simulators in terms of their advantages and limitations is written in Table 2.4.

[1]These features are only available through an extra library which is called INET.

Table 2.3: Features comparison of ns-3 and other network simulators.

Simulator \ Properties	Programming language	Open source	Object oriented	Discrete event	Energy model	Wi-Fi support	Emulator	Contribution	EH support	IoT support
ns-2	C++/OTcl	✓	✓	✓	✓	✓	✓	✓	✗	✓
QualNet	C++	✗	✗	✓	✓	✓	✓	✓	✗	✓
Cooja	C/C++	✓	✓	✓	✓	✓	✓	✓	✓	✓
GloMoSim	Parsec	✓	✓	✓	✗	✓	✗	✗	✗	✗
OMNeT++	C++	✓	✓	✓	✗[1]	✗[1]	✗[1]	✗	✗[1]	✓
OPNET++	C/C++	✗	✓	✓	✗	✓	✗	✓	✗	✓
J-Sim	Java	✓	✓	✗	✓	✗	✓	✓	✗	✗
NetSim	C#/Java	✗	✓	✓	✓	✓	✓	✓	✓	✓
Simulink®(MATLAB)	C/C++	✓	✓	✓	✓	✓	✓	✗	✓	✓
ns-3	C++	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2.4: Wireless simulators comparison in terms of advantages and limitations.

Simulators	Advantages	Disadvantages	References
ns-2	Modularity Support of various platforms	Low speed execution Complex models for real systems	(53, 54)
QualNet	Parallel execution	High complexity to install in Linux Expensive	(55, 65)
Cooja	Strong focus on low power IoT devices	Low speed execution High complex configuration	(56, 66)
GloMoSim	Parallel execution	Lack of excellent documentation	(57, 67, 68)
OMNeT++	Modularity	Not support various protocols	(58)
OPNET++	High speed execution	Not practical for simulations with stable conditions after long time/Low accuracy	(59, 69)
J-Sim	Support of various platforms	Lack of flexibility due to Java regulations	(60, 70)
NetSim	High accuracy Flexibility	Expensive Low speed execution	(61, 62, 71, 72)
Simulink ®(MATLAB)	Easy to debug	High computer resources Complex core code contribution	(63, 73, 74)
ns-3	All the aforementioned advantages	Moderate complexity Require maintainers	(75)

2.5.1 Basic ns-3 Modular Architecture

The overall workflow of ns-3 can be explained as follows: First, the problem is defined. Then the experiment is described through modeling and scenario generation. In the next step, ns-3 executes the code as the executive manager. Lastly, the managed results are obtained as output data. However, before we start to explain the evaluation based on simulations, it is essential to understand the modular architecture of the Wi-Fi-based node in ns-3. As we mentioned earlier, in ns-3, each IoT protocol stack layer is designed modularly. We depict the basic architecture of a Wi-Fi-based node in Figure 2.6, and then we will explain each module separately.

1. **Wifi channel Model**:

   As shown in Figure 2.6, the bottom layer of a Wi-Fi node architecture is the WifiChannel. This layer is responsible for transmitting the signal from one node to another on the same Wi-Fi channel. Additionally, the PropagationLoss and PropagationDelay models are the two main settings of WiFiChannel. These two models are implemented based on the YansWifiChannel (76).

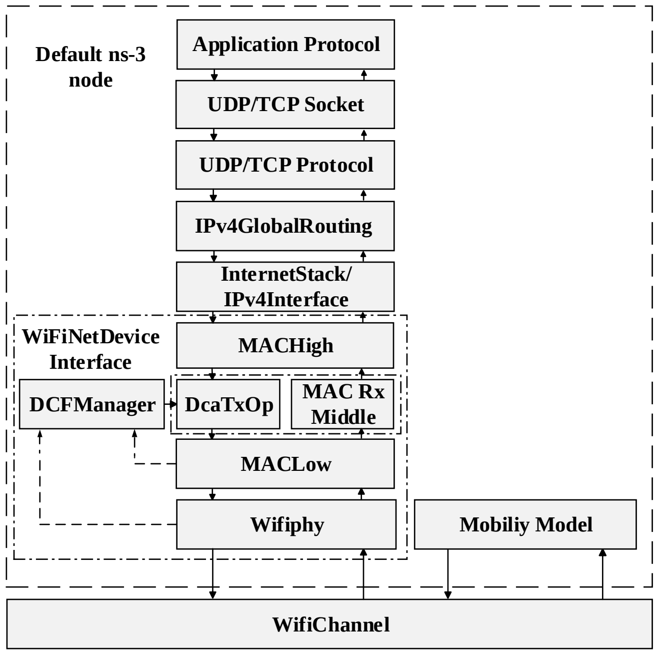


Figure 2.6: The default layered architecture of a sensor node in ns-3.

(a) YansWifiChannel: The class *YansWifiChannel* models the WifiChannel 802.11 and collaborates with the WifiPhy class. The helper class YansWifiChannelHelper is part of WifiChannel. The default WifiChannel model is a channel with the PropagationDelay model equal to the speed of light (ConstantSpeedPropagationDelayModel) and the PropagationLoss model equivalent to the log distance model (reference loss of 46.6777 dB at 1m), which is named LogDistancePropagationLossModel.

(b) PropagationDelay model: This class implements two models, the *RandomPropagationDelayModel*, and the *ConstantSpeedPropagationDelayModel*. Every time the model is invoked in the first model, a new propagation delay that is fully random is generated. All packets, including the transmitted ones between two fixed nodes, encounter a random delay. As a result, the transmitted packets are not in order. In the second one, the signal moves at a constant, light-speed rate. The transmitter and receiver locations are used to compute the delay. The Euclidean distance separates the antenna of the transmitter and the receiver. This model takes into account that the earth is flat.

(c) PropagationLoss model: The ns-3 defines different propagation loss models, which consider the transmit power and the relative positions of the sending and receiving antennas when calculating the reception power. Readers interested in further details of the propagation loss models are referred to (77, 78).

According to the *FriisPropagationLossModel* in ideal conditions, it enables nodes to predict the power level that will be received while taking a distance into account. Specifically, there must not be any barriers close to the channel that might interfere with electromagnetic propagation.

In the *ThreeLogDistancePropagationLossModel* the same concept as LogDistancePropagationLossModel is used, but it takes into account three distances (close, medium, and far) with various exponents. The transmission power is returned when the path loss is requested at a distance shorter than the reference distance. The reference distance is set by default to 1 m.

The propagation occurrence inside a building is modeled based on the *BuildingPropagationLossModel*, in which the shadowing and propagation losses of external and internal walls are taken into account. Two different propagation loss models are built based on this model, *OhBuildingsPropagationLossModel* and *HybridBuildingsPropagationLossModel*. The first model adds the OkumuraHataPropagationLossModel into the building model. The second model is a combination of different models considering frequencies from 200MHz to 2600MHz for various environments, including open areas, suburban and urban. Moreover, it considers the position of the node that can be placed inside or outside of the building. Furthermore, the dimension of the city, penetration loss due to the internal and external walls, the rooftop level, and the type of the building (residential, commercial, office) can be defined according to the selected scenario.

2. **Physical layer model**:

The Physical layer model in ns3 includes functions and operations regarding this layer. The physical layer model is primarily in charge of simulating packet receipt, monitoring energy consumption and handling the sleep/wake-up, and it can be implemented based on *YansWifiPhy* class or *SpectrumWifiPhy* class. Typically, packet reception in physical layer model consists of three essential parts: Each packet is probabilistically assessed for successful or unsuccessful receipt. The probability of transmission is calculated based on the amendment specifications (PHY entity, PPDUs), modulation, signal-to-noise ratio, interference, and the state of the physical layer, which can be the TX (transmission of a signal based on its associated MAC), RX (synchronized on a signal and awaiting the final bit before forwarding it to the MAC), CCA_Busy (represent the Clear Channel Assessment which is used for the primary channel), sleep, idle (the physical layer is not in TX, RX, or CCA_BUSY states), switching (the physical layer is switching channels), and off (the radio is powered off and no transmission or reception of frames occur) states. To calculate the right interference power for each packet when a reception choice has to be taken, an object exists that tracks all received signals.

The probability of a successful reception is calculated by using one or more error models that correlate to the modulation and standard. Readers interested in further details of the WifiPhyModel are referred to (76, 79)

(a) YansWifiPhy: This model was first designed based on the IEEE 802.11a and supported IEEE 802.11e specifications. The primary responsibility of the YansWifiPhy is to receive the data frames from the MAC layer and pass them to the YansWifiChannel, which is connected to that physical layer. The YansWifiPhy also takes data packets from the channel and sends them to the MAC layer.

 The procedure of the single MPDU data frame reception in the YansWifiPhy is defined as follows. First of all, the power level of the signal is compared with the power threshold value (RxSensitivity); if the data frame has a power lower than the threshold value, it will be discarded (the default value is set to the thermal noise floor at 20MHz at room temperature). Then, based on a call from the channel, the physical layer starts to receive the preamble. At this step, signal-to-noise monitoring is possible. In the next step, the state of the physical layer is considered, and the data frame is received by starting the preamble detection period if only the physical layer is in idle or reception states. This detection period will end at the end of the preamble if the signal power is strong enough to be received, which means it needs to be above the threshold value (ThresholdPreambleDetectionModel). At this stage, the physical layer goes to CCA_BUSY mode. If the PHY has detected a signal occupying the primary channel with a received power exceeding CcaSensitivity or if the measured energy on the primary channel is above the energy detection threshold CcaEdThreshold, the physical layer goes to CCA_BUSY. The current preamble and the header correction are checked in the following step. Then, with the help of interference and the error models, the correct decoding of the header is checked. Only at this point, the payload reception can be started and the whole data frame reception procedure is completed.

It is worth mentioning that the probability of error (PER) and SINR are calculated based on the observed SNR by the interefernceHelper.

(b) SpectrumWifiPhy: A more comprehensive implementation built on the Spectrum framework used for other ns-3 wireless models is the SpectrumWifiPhy class. In the case of the coexistence of other wireless technologies with WiFi on the same channel, the spectrum enables a perfectly well frequency segmentation of the signal.

3. **MAC layer model**:

According to Figure 2.6, this layer includes two modules which are known as MACLow and MACHigh.

(a) MACLow: This module include *FrameExchangeManager*, *Txop* and *QosTxop* and *ChannelAccessManager* classes. The FrameExchange-Manger class makes the exchange sequences of the data frames according to each amendment of IEEE 802.11 standard possible. Moreover, this class supports data frame aggregation, re-transmission, frame protection (RTS/CTS), and acknowledgment(ACK/BlockAck). Txop controls the data frame queue in the DCF function; similarly, for the EDCA function, QosTxop is used. Also, MACHigh uses the Txop and QosTxop classes for data frame transmission. These two classes are also known as MACMiddle. The ChannelAccessManager is responsible for enabling DCF and EDCA mechanisms. The DCF and EDCA mechanisms are introduced in IEEE 802.11 legacy and IEEE802.11e consequently and are explained in Section 2.2.2.

(b) MACHigh: According to the network architecture, the MACHigh model (upper MAC) includes three classes, *ApWifiMac*, *StaWifiMac*, and *AdhocWifiMac*. As explained in (80) the most straightforward class refers to the AdhocWifiMac, which does not need beaconing, probing, and associating. The StaWifiMac class enables active probing and associating. In the case of beacons are missed, it automatically handles the re-association. In the last class, APs are responsible for periodically generating beacons and managing the associations. The MACHigh model is also responsible for managing the Rate control algorithms.

It is essential to mention that in the layered architecture of ns-3, the combination of physical and MAC layer models is known as the WifiNetDeviceInerface.

4. **Network layer model**:

The next layer of the architecture of a WiFi node in ns-3 is the network layer, which includes two main components *InternetStackHelper* and *Ipv4AddressHelper*. The responsibility of this layer is to add IP addresses and define the routing protocol to the nodes created in the previous steps.

(a) InternetStackHelper: The InternetStackHelper connects nodes with IP addresses and TCP/UDP protocols. Moreover, it provides event monitoring through pcap and ascii tracings.

(b) Ipv4AddressHelper: This helper makes access to the IPv4 implementation possible, such as pairing (adding or deleting) the created nodes with the specific IPv4 address and defining a routing table and routing path to forward the data frames.

5. **Transport layer model**:

   This layer efficiently controls the data transmissions flow through TCP, and UDP is the other communication protocol provided by the transport layer. The *UDP/TCP Protocol* is utilized to create the proper *TCP/UDP sockets*, which are then used to connect to the application layer.

6. **Application layer model**:

   Each created node must associate with an application to generate the traffic and keep track of generated data through the traffic sink. The ns-3 provides applications such as *OnOffApplication*, *bulkSendApplication*, *PacketSink* (completed the OnOffApplication), *UdpClientServer*, and *UdpEcho*. Each application type offers a start and stop time and defines the packet size, application data rate, and specific traffic types.

7. **Mobility Model**:

   The MobilityModel class includes different subclasses that all use the Cartesian coordination system to track the position and speed of the nodes. These MobilityModel subclasses are known as, *ConstantPosition*, *ConstantVelocity*, *ConstantAcceleration*, *GaussMarkov*, *Hierarchical*, *RandomDirection2D*, *RandomWalk2D*, *RandomWaypoint*, *SteadyStateRandomWaypoint*, and *W-aypoint*. In addition this class allocates the initial layout of the nodes as list, Grid, Rectangle, Box, Disc (random and uniform).

2.6 Overview and Categorization of Machine Learning in Wireless Communication

According to computer scientist John McCarthy, the phrase "artificial intelligence" refers to intelligence displayed by machines and was first used in 1956 (81). Building algorithms or models for systems that can automatically learn to make decisions and predictions based on experience and data and improve performance is the goal of a sub-field of the Artificial Intelligence (AI) area known as ML.

Recently, the adoption of ML has increased significantly across various applications. ML algorithms provide great adaptability, flexibility, profitability, and processing capabilities. Since they expand on conventional methods (already used in many industries and research areas), they are gaining popularity in making predictions and making decisions without having to be explicitly programmed. One of the ML application areas is network operation and management. In the domain of networking, ML techniques have been investigated for network security, performance improvement, and traffic engineering (82, 83).

ML techniques are often divided into four major groups depending on the type of information or feedback the learning system has access to.

2.6.1 Machine Learning Categorization

In this subsection, the four ML subcategories known as Supervised Learning (SL), Unsupervised Learning (USL), Semi-Supervised Learning (SSL) and Reinforcement Learning (RL) (84) will be explained, which are summarized in Figure 2.7.

1. **Supervised Learning:**

   The main feature of SL algorithms is that they allocate labels to data sets, to train algorithms to predict the output accurately and deliver to the desired one. This category is separated into two methods, classification and regression.

   (a) Classification: A dataset including input characteristics and their associated labels is used as the starting point for the classification procedure. In the training phase, the algorithm learns to efficiently adjust input features to labels and modifies its internal parameters to minimize prediction errors. After training, the algorithm creates a model that encapsulates the link between labels and features, allowing it to predict values for new data occurrences. As it is shown in Figure 2.7, the following classification techniques are often used: decision tree, k-nearest neighbor, random forests, Support Vector Machines(SVM), logistic regression, and Naive Bayes.

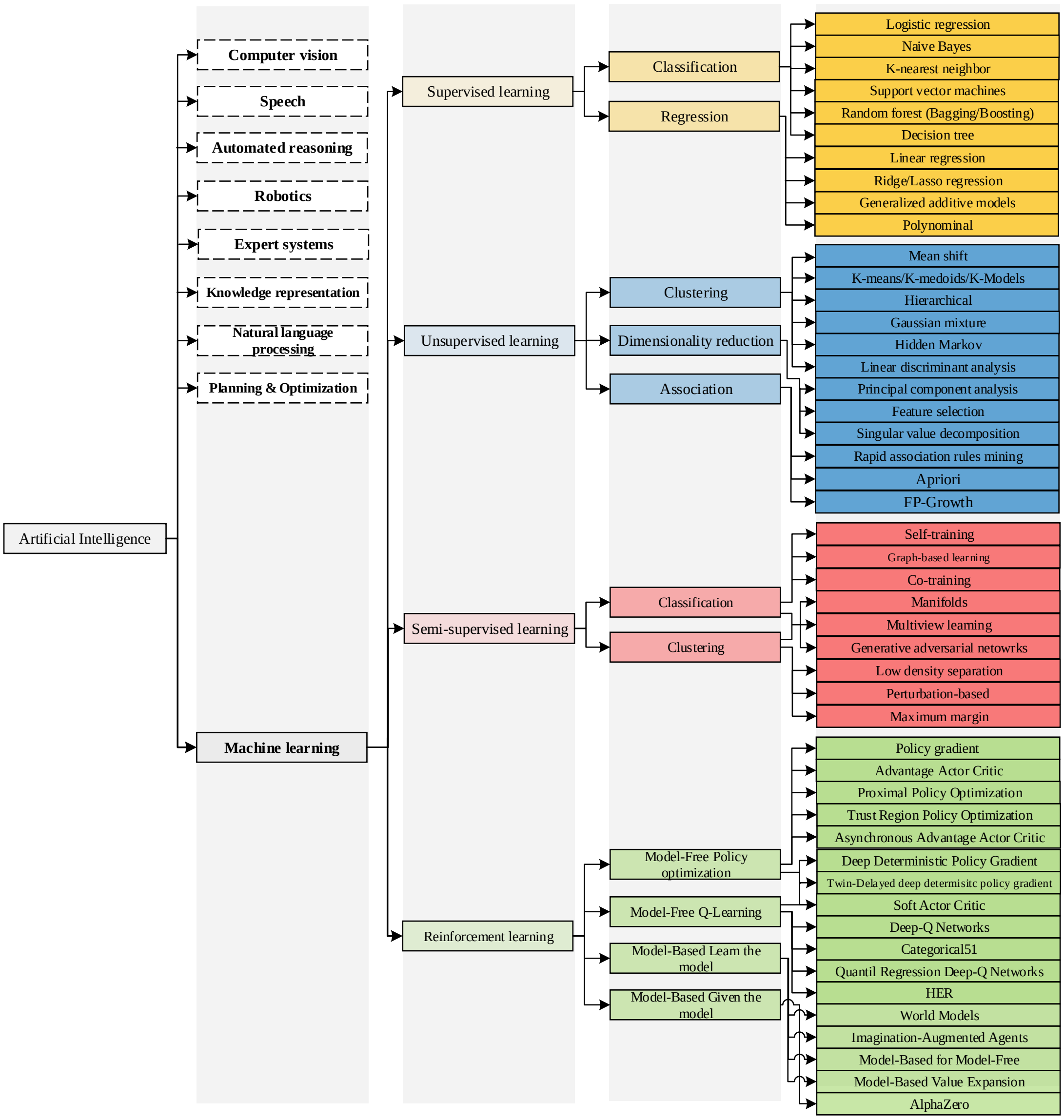


Figure 2.7: The categorization of ML algorithms.

(b) Regression: It is a method for determining how independent traits or variables relate to a dependent feature or output. This method is used for ML predictive modeling, where an algorithm is deployed to forecast continuous outcomes. Popular regression techniques include linear regression, ridge/lasso regression, generalized additive models and polynomial regression (85).

Since the concept of ML entered the field of wireless communication networks, researchers have been trying to introduce intelligent optimization of wireless communication technologies through ML techniques. As the first selected category, SL has been focused on the different wireless communication technologies to elevate them to intelligent systems. For instance, a SL algorithm is proposed in (86), which is able to associate end users to the base stations in a cellular network (5G) in the most efficient way. In another work (87), the authors focus on classifying the behavior detection of the elderly based on KNN, SVM, and logistic regression algorithms while using passive RFID tags. They conveyed that all the classification methods improved the accuracy of the feature detection. SL is also applied in the rate selection in Wi-Fi networks, where the channel condition is used for the rate selection (88).

2. **Unsupervised Learning:**

The main feature of USL is that the methods are applied to unlabeled data sets. According to these algorithms, the output is achieved by identifying hidden patterns and informational similarities and distinctions or data clusters in the input without the assistance of a human. This category is divided into three methods, clustering, dimensionality reduction and association.

(a) Clustering: In clustering the unlabeled data is grouped by using the data mining method based on similarities or differences. The clustering methods are employed to organize raw, unclassified data items into groups that may be seen as patterns or structures in the data. Several types of clustering methods including mean shift, K-means, K-medoids, K-models, hierarchical, Gaussian mixture, hidden Markov, and linear discriminant models (Figure 2.7).

(b) Dimensionality reduction: Although more data often produces more accurate findings, it can potentially affect ML algorithm performance (for instance, overfitting) and make data sets more challenging to visualize. When a given data collection has excessive characteristics or dimensions, this method is utilized. It keeps the integrity of data set feasible while reducing the quantity of data inputs to a tolerable level.

There are several different dimensionality reduction techniques, including Principal Component Analysis (PCA), feature selection, Singular Value Decomposition (SVD).

(c) Association: A rule-based method for identifying connections between variables in a given data set is an association. Although several alternative algorithms, including Apriori, Eclat, FP-Growth, and rapid association rules mining are employed to produce association rules, the Apriori approach is the most often used (89).

According to recent survey research on the role of ML in Wi-Fi communications (83), compared to SL methods, USL methods are less employed in these scenarios. One of the employment of the USL method in Wi-Fi networks is explained in (90), where the authors apply a self-organizing hidden Markov model map (SOHMMM) algorithm to reduce the anomaly detection of an AP, which performs based on the IEEE 802.11 standard. According to the obtained results, their proposed algorithm increases the accuracy of classification and speed of convergence to the optimal. The novelty of their work is that they provide a real-time diagnostic approach for anomaly detection on Wi-Fi. Also, the USL method has been applied to LPWAN scenarios. For instance, in (91), the K-means clustering-based algorithm is defined to reduce the delay and collision while increasing the throughput in a dense LoRa network. Another example of this category is presented in (92), where the authors proposed an Indoor Wireless Localization based on Unsupervised Learning (IWLUL) algorithm based on the hierarchical Bayesian hidden Markov mode. In this work, the localization of mobile devices is accomplished based on the received signal strength of the devices with a high level of accuracy.

3. **Semi-Supervised Learning:**

Semi-supervised learning is a method of ML that, during training, merges a considerable amount of unlabeled data with a small amount of labeled data. Semi-supervised learning category is between SL (with labeled training data) and USL (with only labeled training data), in which, combined with a tiny quantity of labeled data, unlabeled data can significantly increase learning accuracy. This category is divided into two methods, classification and clustering.

(a) Classification: Semi-Supervised Classification (SSC) is similar to the Supervised algorithm. In contrast to a supervised algorithm, it classifies a lot of test data with less training data. To lower the cost and length of the data set construction, it is feasible to use less training data while utilizing this semi-supervised classification. Some of the techniques that belong to this category are, self-training, graph-based learning, and co-training.

(b) Clustering: Semi-supervised clustering is a unique variant of unsupervised clustering. Although in unsupervised clustering, the unlabeled data patterns are used for clustering, in semi-supervised clustering, some information together with labeled and unlabeled data as pair-wise constraints are considered, which aids in grouping the data patterns. Three techniques of this category are known as low density separation, Perturbation-based, and maximum margin (93).

Some other techniques, such as multi view learning, manifolds, and generative adversarial networks, are considered a combination of semi-supervised classification and clustering methods to achieve better accuracy (93). In the literature, some researchers have been trying to benefit from the advantages of the SL and USL methods and defined SSL-based optimization algorithms. One example of this category is proposed by Thapaliya et al. (94), where the outcomes of different SL-based algorithms are provided to the USL-based algorithm to estimate the network congestion level more accurately in a Wi-Fi scenario. Another example of applying the SSL method in a Wi-Fi network is provided in (95), which considers congestion issues in a dynamic environment. For this reason, first, they apply different SL-based algorithms to extract the features of the locations with various congestion levels. Then, based on the USL methods, they cluster the congestion levels in specific groups. The authors in (96) applied the SSL-based algorithm in a heterogeneous network where the energy level is used to accurately predict the co-channel interference in the coexistence of the cellular network (LTE) and Wi-Fi networks. SSL method is also applied in other wireless communication technologies rather than Wi-Fi, such as Long Range (LoRa) (97) communication, the coexistence of Wi-Fi and Bluetooth (98), and cellular network (99). The performance of these proposed algorithms is evaluated through mathematical analysis or employed in a test bed. Nevertheless, non of these algorithms are able to learn from the current knowledge and make decisions intelligently. Thus to fill this gap RL-based algorithms are introduced.

4. **Reinforcement Learning:**

RL is the last category of ML, which fundamentally includes two main entities: environment and agent. In contrast to the previous ML categories, RL can learn to interact with the environment through the agent based on its experiences, and finally reach the optimal point of the selected target (reward). As it is shown in Figure 2.8, the environment consists of the model (network model), which provides a set of observations (state, S_t), and then the agent takes action and makes a decision (A_t) based on the observation. Then, the reward function (a signal as feedback, R_t) is provided as a feed of action to the agent entity to determine how far the algorithm is from the desired optimal value. The agent retains the RL algorithm and updated policies at each time or event interval to maximize the performance of the system.

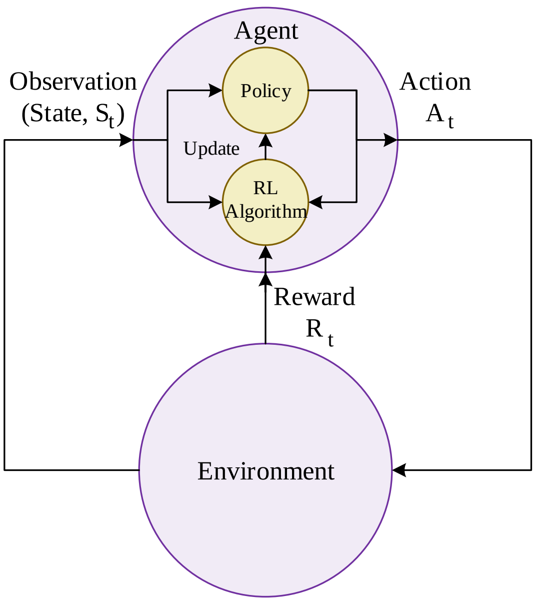


Figure 2.8: The general framework of the reinforcement learning algorithms.

RL is separated into two main subcategories: model-based and model-free methods. The model-free learning methods gains action values based on reward prediction errors (RPEs). By using an RPE, the action value—the anticipated reward associated with certain activity—is updated to increase the precision of the value estimate. In contrast, model-based methods consider the values of future states as opposed to present actions, for this reason they need to connect to the external structure of the environment rather than the internal structure of the model (100).

(a) Model-Free: Training the agent in this method is accomplished by two main approaches: *Policy Optimization* and *Q-Learning*. Techniques built on the first approach clearly reflect a policy. They either directly or indirectly maximize the required parameters through gradient ascent on the performance target or by maximizing local approximations of the performance objective. Most of the time, this optimization is carried out on-policy, meaning that each update only makes use of information gathered while operating in accordance with the most current revision of the policy. To determine how to update the policy, policy optimization usually includes learning an approximator for the on-policy reward function. According to Figure 2.7, some techniques that belonging to this method are known as, Advantage Actor Critic (A2C) and Asynchronous Advantage Actor Critic (A3C) which by applying gradient ascent can maximize performance directly. In contrast, the updates of Proximal Policy Optimization (PPO) technique do not directly optimize performance but rather maximize a surrogate objective function that provides a cautious estimate of the change in the approximation goal due to the update. Other techniques are policy gradient and Trust Region Policy Optimization (TRPO).

The second approach is used to develop techniques that train an approximator for the optimal action-value function. In general, the Bellman equation-based goal function is used in these techniques. Therefore, as a result, each update can incorporate data gathered at any time during training, regardless of how the agent was selected to explore the environment at the time the data was gained. This optimization is most of the time carried out off-policy. This method includes techniques such as Deep-Q Networks (DQN) which consider the basic technique of deep RL, Categorical51 (C51), Quantil Regression Deep-Q Networks (QR-DQN), and HER.

Alongside the aforementioned techniques, there are others such as Deep Deterministic Policy Gradient (DDPG), Twin-Delayed Deep Deterministic Policy Gradient (TD3), and Soft Actor Critic (SAC). These techniques perform based on the combination of the policy optimization and Q-learning which try to improve the specific advantage of each approach and balance the trade-off between them.

In general, techniques based on the first approach provide a direct, stable and reliable optimization, whereas the second approach applies an indirect and sustainable optimization.

(b) Model-Based: The RL model-based methods can be separated into two approaches: *Learn the Model or Learned Model* and *Given the Model or Known Model*. Despite the model-free methods, model-based methods do not have a simple defined cluster approach, and they are able to provide numerous techniques. The simplest approach of this method (pure planning) chooses actions by using just pure planning techniques like model-predictive control (MPC), and it never explicitly representing the policy. In MPC, in each iteration the agent computes an optimum plan in relation to the model based on the observations. The plan then outlines the actions to be taken over a specific iteration following the present (the planning algorithm may consider future rewards beyond the horizon through the use of a learned value function). The agent then takes the first part of the plan before tossing the others. Every time it becomes ready to interact with the environment, it computes a new plan to prevent utilizing an action from a plan with a shorter planning horizon than intended. Some other examples of model-based learn the model method are known as, Model-Based for Model-Free (MBMF), world models, Model-Based Value Expansion (MBVE), and Imagination-Augmented Agents (I2A).

One of the approaches that belong to the model-based approach is the expert iteration approach, which uses and learns an explicit representation of the policy. The agent takes samples from its present policy and creates candidate actions for the plan using a planning technique (like Monte Carlo Tree Search) in the model. The planning algorithm is an "expert" on the policy since it generates an action superior to what the policy alone would have generated. The policy is then modified to result closer to the planning algorithm's output. The techniques which follow this approach are Large Language Models (LLMs) and AlphaZero (101).

In contrast to the previous categories, RL recently attracted more attention among researchers in the wireless communication networks area. The reason is that RL methods are capable of solving more complex problems than other ML categories. They are able to correct the errors through the training process in which the long-term results are more accurate and reliable, and closer to the human learning process. Solving a problem does not need to include a training process because it learns from experience. In particular, in the case of Wi-Fi networks, since the new and upcoming amendments of IEEE 802.11 have introduced new features and increased the density and complexity of the Wi-Fi network (distributed management and deployment), the deployment of RL methods in wireless networks is becoming more attractive. It is worth mentioning that including the ML learning features to improve the performance of Wi-Fi networks is under discussion for IEEE 802.11be amendment and beyond (102).

Specifically, RL methods can be applied to the core features of the Wi-Fi networks, such as optimization of the CW value (103), transmission time slot (104), data rate adaptation (105, 106), and frame size (107), or recent features such as beamforming (108, 109), multi-user communication (110), spatial reuse (111, 112), channel bonding (113, 114), and MIMO networks (115). Other works focus on Wi-Fi management, such as channel and band selection (116, 117), and management architecture (118). Rather than employing RL methods in Wi-Fi scenarios, RL methods have been applied to LPWAN networks such as (119, 120). In these works, the RL methods reduce the required energy for the systems.

Table 2.5 compares the available research in different categories of ML in the literature.

2.6.2 Machine Learning Tools

In recent decades, different ML tools have been introduced that make the usage of ML more accessible for researchers in distinct fields, from marketing management and stock analysis to computer vision, speech recognition, and network engineering. Since this thesis use ns-3 simulator as the evaluation tool, OpenAI Gym as one of the available tool-kits which has been integrated with ns-3. The features of this tool are explained in this section.

1. **OpenAI Gym:** Fundamentally, OpenAI Gym is a toolkit that is capable of creating new ML algorithms in a range of simulated environments (such as Atari games, board games, 2D and 3D physical simulations). Thus, algorithms can be developed and then evaluated without the requirement of implementing a specific environment from scratch.. OpenAI Gym provides a user-friendly platform to integrate AI projects. Readers interested in further details of the OpenAI Gym are referred to (121).

2. **ns3-gym:** As shown in Figure 2.9, ns-3 gym consists of three main parts, the first part is the OpenAI Gym module, which controls the agent actions and is developed in Python. The second part is the environment, which corresponds to the ns-3 simulator and is provided in C++. The third part is known as the ns-3 gym interface, which is responsible for providing the connection between the environment and the agent and interpreting the agent to understand the output of the environment, and vice-versa. In addition to the observation space, the action space, game over conditions (when the RL algorithm must stop), and reward (the desired optimal value) need to be defined in the environment part. Then, through the ns-3 gym interface, which takes action behind the scene (in this case, ZMQ library), the observation values are sent to the agent, and the agent makes the decision based on these values.

Table 2.5: Features comparison of related work on different ML categories.

Studies \ Properties	ML category	ML mechanism	Wireless technology	Evaluation method	ML application	Year
(86)	SL	NN	Cellular network	Simulation	Association to the best BS	2020
(87)	SL	K-NN,SVM,LR	RFID	Simulation+Test	Classifying RSS	2021
(88)	SL	Random forest	Wi-Fi	Simulation+Test	Link adaptation	2018
(90)	USL	SOHMMM	Wi-Fi	Simulation	Anomaly detection reduction	2021
(91)	USL	K-means	LoRa	Simulation	Collision and delay reduction Throughput increment	2019
(92)	USL	IWLUL	Zigbee	Mathematical Analysis+Test	Maximize the accuracy of indoor localization	2016
(94)	SSL	Clustering	Wi-Fi	Test	Congestion level prediction	2018
(95)	SSL	Classification	Wi-Fi	Test	Performance improvement	2019
(96)	SSL	Classification	Wi-Fi	Test	Carrier Sense Adaptive Transmission (CSAT)	2020
(97)	SSL	DNN	LoRa	Mathematical analysis+Test	Maximize the accuracy of outdoor localization	2021
(98)	SSL	FSELM	Wi-Fi+Bluetooth	Mathematical analysis+Test	Higher indoor location accuracy	2018
(99)	SSL	Cross validation Distribution estimator	Cellular network	Test	Anomaly detection improvement	2018
(103)	RL	QL	Wi-Fi	Simulation	CW-based optimization	2021
(104)	RL	Multi-Agent RL	Wi-Fi	Simulation	Transmission time slot	2022
(105)	RL	TS	Wi-Fi	Simulation	Guard interval adaptation	2020
(106)	RL	QL	Wi-Fi	Simulation	Transmission rate adaptation	2021
(107)	RL	ϵ-greedy	Wi-Fi	Simulation	Frame size optimization	2019
(108)	RL	DRL	Wi-Fi	Mathematical analysis	Link outage prediction	2019
(109)	RL	DRL	Wi-Fi	Simulation	AP and band adaptation	2021
(110)	RL	DQN	Wi-Fi	Simulation	RUs scheduling	2020
(111)	RL	QL	Wi-Fi	Simulation	Transmit concurrently or not	2019
(112)	RL	MAB	Wi-Fi	Simulation	Txpower+sensitivity threshold adaptation	2021
(113)	RL	DQN	Wi-Fi	Simulation	Channel+bandwidth adaptation	2020
(114)	RL	MAB	Wi-Fi	Simulation	Channel+bandwidth adaptation	2021
(115)	RL	DDPG,Monte-Carlo policy gradient	Wi-Fi	Simulation	Channel and cluster APs selection	2019
(116)	RL	MAB	Wi-Fi	Simulation	Association to the best AP	2019
(117)	RL	DQN	Wi-Fi	Simulation	Handover decision	2019
(118)	RL	DQL	Wi-Fi	Simulation	Slicing optimization	2019
(119)	RL	ϵ-greedy, Weighted average Thompson sampling	LoRa,NB-IoT, Sigfox	Simulation+ Test	Consumed energy reduction	2022
(120)	RL	Temporal difference (TD)	Mesh IoT	Simulation	Routing energy reduction	2019

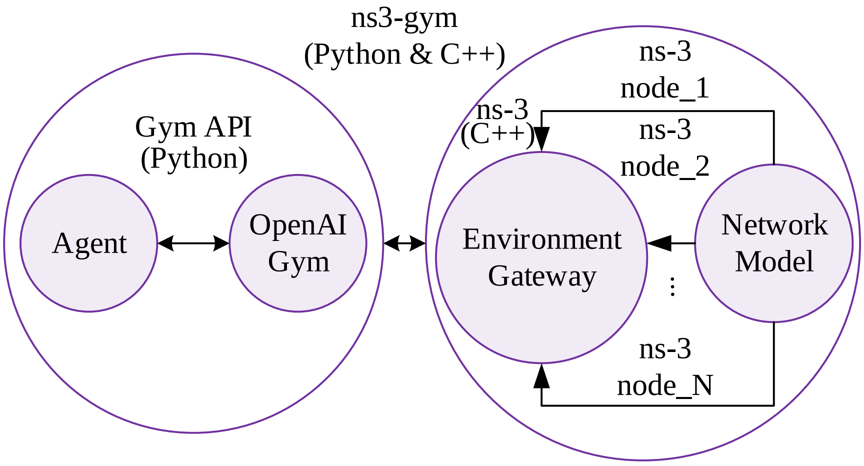


Figure 2.9: The framework of the ns3-gym (3).

2.7 Chapter Summary

This chapter categorized the existing energy-aware MAC protocols. Then it examined the present wireless communication technologies and their current MAC layer characteristics, along with several MAC optimization methods for each technology. Since the MAC layer operations are relatively energy-hungry, by focusing on their optimization, the energy consumption of the considered system can be reduced. Moreover, this chapter listed the most relevant energy harvesters for the IoT paradigm. Since solar energy harvesters can be deployed in both outdoor and indoor environments, providing a significant amount of energy relative to their size (it will be discussed in Section 5 of Chapter 3), and their form factor adaptability, makes them one of the most promising options for IoT devices.

The selection of the most appropriate simulation environments for the Thesis was guided by an extensive comparison of various network simulators, which is detailed in Tables 2.3 and 2.4. This comparison not only supports our choice but also provides a solid foundation for the Thesis. In summary, ns3 is an open-source network simulator that makes collaboration and customization possible. Moreover, it provides a high level of realism, capability of simulating large-scale networks, and seamless integration with real-world tools to facilitate validation and experimentation, which is crucial for accurately evaluating the performance of new network protocols and technologies. Finally, its modular nature and extensibility enable easy integration of new models and algorithms, ensuring relevance across diverse research networking areas. Given that one of the objectives of this Thesis is to illustrate how optimization scenarios can leverage ML techniques, in this chapter, we elaborated on the relevant state-of-the-art ML approaches.

Additionally, the potential integration of ns3 with OpenAI Gym is discussed as a means to enhance the exploration of ML methodologies (RL in this case) in network optimization.

The thorough explanation of the existing energy-aware MAC protocols categorization, together with the relevant EH technologies and analysis of energy models, will be presented in the next chapter, helping clarify the energy needs and shortages of IoT systems in wireless communication technologies. The next chapter will also show the preeminence of wireless communication technologies within the IoT paradigm. Then, the appropriateness of the explained energy harvesting technologies for wireless communication technologies in the IoT paradigm will be investigated. Additionally, the categorized energy harvesting MAC protocols will be compared in the next chapter, and an assessment of the actual energy usage of the various IoT system layers with an emphasis on MAC layer operations will be given. This dissertation will outline the energy lost due to MAC anomalies, establishing the crucial factors enabling MAC layer energy harvesting strategies. Detailed guidance for open problems and research obstacles for energy harvesting MAC protocols within IoT devices will be provided.

To the best of our knowledge, this dissertation is the first to study the compatibility of IoT communications with readily accessible energy harvesters from a MAC layer perspective in an organized manner.

3

A Comprehensive Review on Energy Harvesting Integration in IoT Systems from MAC Layer Perspective: Challenges and Opportunities

This chapter includes contributions regarding investigating the possibility of EH integration in the IoT ecosystem and the existing gap in the literature, which was published as a journal article in *Sensors, MDPI*. Specifically, it thoroughly studies existing energy-aware MAC protocols, focusing on their functionality, benefits, and limitations. It also examines the compatibility of wireless communication technologies with IoT and their MAC layer features. The research also examines energy consumption across different levels of IoT systems and identifies energy wastage caused by MAC anomalies. Finally, it provides guidelines to address open issues and research challenges in EH MAC protocols.

sensors

MDPI

Review

A Comprehensive Review on Energy Harvesting Integration in IoT Systems from MAC Layer Perspective: Challenges and Opportunities

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Abstract: The Internet of Things (IoT) is revolutionizing technology in a wide variety of areas, from smart healthcare to smart transportation. Due to the increasing trend in the number of IoT devices and their different levels of energy requirements, one of the significant concerns in IoT implementations is powering up the IoT devices with conventional limited lifetime batteries. One efficient solution to prolong the lifespan of these implementations is to integrate energy harvesting technologies into IoT systems. However, due to the characteristics of the energy harvesting technologies and the different energy requirements of the IoT systems, this integration is a challenging issue. Since Medium Access Control (MAC) layer operations are the most energy-consuming processes in wireless communications, they have undergone different modifications and enhancements in the literature to address this issue. Despite the essential role of the MAC layer to efficiently optimize the energy consumption in IoT systems, there is a gap in the literature to systematically understand the possible MAC layer improvements allowing energy harvesting integration. In this survey paper, we provide a unified framework for different wireless technologies to measure their energy consumption from a MAC operation-based perspective, returning the essential information to select the suitable energy harvesters for different communication technologies within IoT systems. Our analyses show that only 23% of the presented protocols in the literature fulfill Energy Neutral Operation (ENO) condition. Moreover, 48% of them are based on the hybrid approaches, which shows its capability to be adapted to energy harvesting. We expect this survey paper to lead researchers in academia and industry to understand the current state-of-the-art of energy harvesting MAC protocols for IoT and improve the early adoption of these protocols in IoT systems.

Keywords: Internet of Things; wireless communication technologies; MAC layer operations; energy harvesting MAC protocols; energy models; energy neutral operation

1. Introduction

The Internet of Things (IoT) enables the connection and data transferring over the Internet for a massive number of physical objects, which are equipped with distinct hardware and software to enhance a wide range of applications and services [1]. These enhancements as part of the IoT paradigm aim at adding value to every aspect of human life and society, from digital hospitals in healthcare services to process management in industrial automation [2]. According to the Cisco Annual Internet Report [3], it is expected that the number of connected devices will increase from 18.4 billion in 2018 to 29.3 billion devices by 2023. Hence, providing sufficient energy to maintain this massive number of connected devices will be a challenging . The analysis from "The Shift Project" [4] conveys that the increasing trend of IoT connected devices leads to a Computational Annual Growth Rate of 4.5% in the expected energy consumption of IoT deployments (from 2312 TWh in 2015 to 4350 TWh in 2025). According to these predictions, in the near future, powering up IoT devices with conventional batteries with a limited lifetime, which requires frequent replacement, is a concerning issue and may cause system failure [5]. Moreover, since IoT systems have spread across many different use cases, from healthcare and industrial to transportation and residential, end devices may be located in hard to reach and hazardous areas, where the maintenance and frequent conventional batteries replacement make the usage of them inefficient and costly [6]. This means each year, billions of batteries are accumulated in landfills, which negatively impact the environment, such as ecotoxicity and water pollution.

The limited lifetime of the conventional batteries, which increases the maintenance cost, number of replacements, and negative impact on the environment, in a system with a few devices do not raise an issue, whereas, in networks with millions or even billions of devices, it becomes a significant issue. Since these battery limitations threaten the rapid development of the IoT paradigm, academia and industry have become interested in extending the lifetime of IoT devices while maintaining optimal performance. For this purpose, power management techniques, including energy-efficient methods (e.g., light-weight protocols, scheduling optimization, and low power transceivers) or energy harvesting techniques (e.g., ambient energy harvesting, and dedicated energy harvesting) [7], and energy conservation methods in IoT devices are currently hot topics. Alongside the energy-efficient techniques, which reduce the networks' energy consumption, recent innovations in IoT technologies such as portable devices with small batteries lead to introducing energy harvesting technologies as a promising solution to provide enough energy for them [8] and prolong the lifetime of the network. The authors in [9] emphasized the fundamental role of energy harvesting technologies in IoT systems by imparting that the increasing interest of academia and industry in energy harvesting technologies leads to a growth in the energy harvesting global market from 360.6 million dollars in 2020 to 987.09 million dollars by 2028.

Although energy harvesting technologies provide more energy to IoT systems, to satisfy their possibility of integration with IoT systems, some parameters such as size, type of the end-user device, and IoT application need to be taken into account. To understand how energy harvesting technologies are envisioned to be supported in IoT, different authors in the literature [10,11] provide the schematic in Figure 1. This figure is based on these papers, which lists the key components required to support energy harvesting at the IoT system's sensor level. The top layer is responsible for harvesting energy. Three parts of the bottom layer make wireless communication possible, manage the entire device, and include sensors and actuators (from right to left). In systems like Figure 1, the Energy Neutral Operation (ENO) condition is achieved if the energy harvester provides energy greater than or equal to the required energy of the system. However, fulfilling this condition under specific considerations (e.g., small size of the energy harvester) and the whole system's requirements remains a gap in the literature.

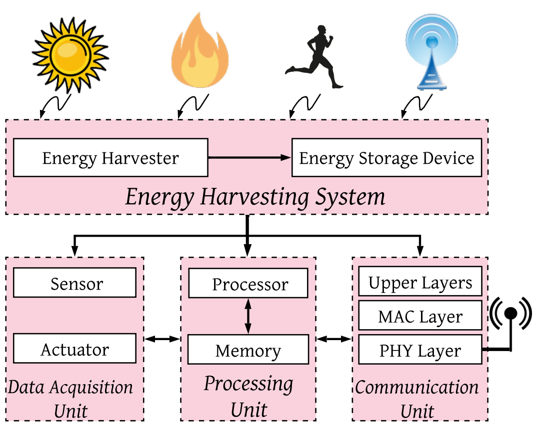
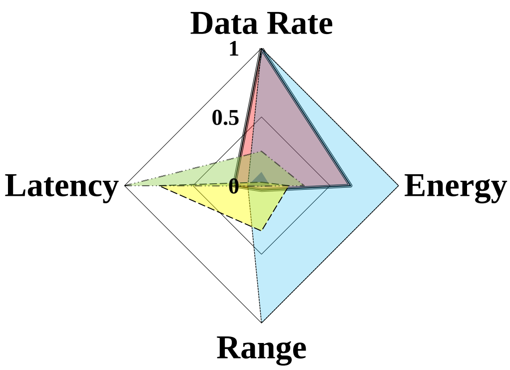


Figure 1. General schematic of an IoT node equipped with energy harvesting.

1.1. Motivation

The increasing trend in the number of connected devices in the IoT paradigm suggests that powering up these devices with conventional batteries requires frequent battery replacement, which is not efficient and leads to environmental contamination. Hence, there is a need to improve the efficiency of IoT technologies to be able to prolong the lifetime of these systems. However, due to the different characteristics of each IoT technology, achieving this sustainability improvement is a challenge.

The IoT market is providing different wireless communication technologies to support the various Key Performance Indicators (KPIs) of the IoT applications at the communication level (cf. Figure 2). Depending on the implemented wireless communication technology, each IoT system will have different performance requirements, where energy consumption is one of the most critical aspects. Hence, there is the need to study energy consumption in different IoT wireless communication technologies to understand its impact on IoT performance. Since there is no proper characterization of these technologies in terms of energy requirements in the literature, there is a need for a unified energy model approach. After understanding the energy requirements at the IoT communication level, different solutions to improve the sustainability of the IoT systems towards the ENO property can be introduced. Within the available solutions, energy harvesting is a popular one for improving sustainability in IoT. However, based on the current literature, the energy provided by energy harvesting is not always sufficient with the IoT communication technologies because of the limited and intermittent behavior of energy harvesting energy sources. Hence, the challenge is to integrate energy harvesting in wireless communication technologies without impacting the system's performance.



IoT Sectors		Data Rate (Kbps)	Energy (mJ)	Range (m)	Latency (ms)
Smart Healthcare	■	100	1.25	25	10
Industrial Automation	■	1000	13	100	20
Smart Transportation	■	1000	20	3000	10
Agricultural Monitoring	■	25	4	1000	75
Smart Buildings	■	250	6.22	10	100

Figure 2. Different KPIs for IoT use cases [12–18].

For successful integration of energy harvesting within IoT systems, there is the need to optimize the energy consumption in wireless communication technologies at different IoT layers. For instance, an adaptation to the channel condition or energy-aware routing protocols can optimize the energy consumption level at the physical and network layer, respectively. Nevertheless, since the Medium Access Control (MAC) layer is responsible for scheduling the data frame transmissions and faces fundamental communication challenges (e.g., collision frames, the overhead of control packets, idle listening, unused idle slots, synchronization, and others), it consumes most of the energy budget of wireless communications. Thus, there is the need to adapt this layer to make the IoT systems sustainable and compatible with energy harvesters while keeping these modifications compatible with existing wireless technologies.

1.2. Contribution

As highlighted in the introduction of this survey, the MAC layer in wireless communication has an essential role in optimizing the IoT systems' energy usage. To understand the characteristics of different MAC mechanisms and their limitations in the IoT scenario, a MAC categorization is necessary. Since there are diverse wireless technologies already being deployed at the communication level of the IoT systems, to understand the requirements of each technology in terms of energy, given that MAC layer operations are power-hungry, the analysis of energy consumption needs to be performed based on these operations. The study of energy consumption for communication technologies is achieved by energy consumption models, which can be obtained based on real hardware measurements, simulations, or analytical models. Before explaining the already existing energy harvesting-based MAC modifications and enhancements in the wireless communication technologies literature, together with their benefits, drawbacks, and compatibility between energy harvesters and its application to the different IoT use cases, it is necessary to estimate the amount of energy that each energy harvester provides to the system. Thus, the characteristics of the energy harvesters and their energy sources need to be studied. We expect the provided information lead the researchers in academia and industry to understand the limitations of the existing works and promote a change of thinking for early adoption of energy harvesting techniques within the IoT paradigm.

In this survey paper, we searched for the most relevant articles in available databases among the high-quality journals and conferences and their relevant references that were cited papers during the past two decades. We organized our search based on a selected keyword list which includes the most common and relevant keywords to this topic. To the best of our knowledge, the wireless communication technologies of the IoT paradigm have not been compared based on their actual amount of power consumption before in the literature. Also, to the best of our knowledge, the compatibility of IoT communications with available energy harvesters is studied from a MAC layer perspective in a structured manner for the first time in our survey paper. To summarize, this survey paper includes the following contributions:

- We extensively review the already existing energy-aware MAC protocols to develop a categorization that identifies the various dimensions of proposed MAC additions to enable the concurrent use of energy harvesting.
- We comprehensively study the available wireless communication technologies to highlight their compatibility with the IoT paradigm and their existing MAC layer features, accompanied by different MAC optimization techniques for each technology. Our work takes current literature to develop a unified approach to analyze energy models, contributing to a better understanding of energy requirements and shortages of the IoT systems in terms of wireless communication technologies.
- We contribute with an analysis of the functionalities and characteristics of existing energy harvesters and their suitability for the wireless communication technologies in the IoT paradigm.
- We thoroughly study the functionality of existing energy harvesting MAC protocols in the literature, their benefits and drawbacks, to understand the available integration of energy harvesting techniques at the MAC layer and their limitations.
- We comprehensively review the energy consumption of the different levels of IoT systems with a focus on the MAC layer operations. This study specifies the energy wastage through MAC anomalies, which determines the essential considerations to enable energy harvesting techniques at the MAC layer.
- We provide an extensive guideline for open issues and research challenges for energy harvesting MAC protocols within IoT systems.

The remainder of this paper is organized as follows. In Section 2 the state of the art of this paper is highlighted. Section 3 presents the categorization of the energy-aware MAC protocols for IoT systems. Then potential wireless communication technologies and their energy models for IoT systems are explained in Section 4. Section 5 is described the available energy harvester technologies and their applicability with IoT systems. The existing energy harvesting MAC protocols in the literature are categorized based on their mechanisms and then explained in Section 6. Some challenges regarding the MAC layer and open research directions and future works are highlighted in Section 7. In the end, in Section 8 some final remarks are given.

2. State of the Art

There are numerous existing MAC protocols in the literature, where each of them has distinct benefits and drawbacks. To meet the requirements of the existing wireless communication technologies, specifically in terms of energy consumption, the MAC layer protocols of these technologies may adopt different mechanisms. However, the defined MAC protocols, for the current wireless communication technologies, do not consider the energy harvesting paradigm in their design procedure. Thus, to support energy harvesting techniques on the specific MAC protocol, it is necessary to understand the implications of these techniques on the benefits and drawbacks of that protocol. The first step to understand these requirements is to review the available energy harvesting MAC protocols in a structured way. In the past decade, several studies have defined various categorizations for the energy harvesting MAC protocols in IoT systems and highlighted the requirements of different MAC mechanisms to support energy harvesting technologies. This section will explain the related works regarding these categorizations.

One of the earliest studies that explored the possibility of enabling energy harvesting techniques in the MAC layer of IoT systems by reviewing previous works was proposed in [19]. In this work, the authors explain the role of energy harvesters in IoT systems and the requirements of these networks. The proposed energy harvesting MAC classification was built based on the adopted optimization techniques in designing the protocols, such as load balancing, contention reduction, or wake-up time awareness. In this work, the authors study the approaches of the MAC protocols which have enabled the available ambient energy harvesting methods, and then they highlight the strengths and drawbacks of each energy harvesting MAC protocol. Although the authors provide detailed information about the functionality of the selected protocols, the selection of state-of-the-art requires an update to include all the existing energy harvesting MAC protocols in the literature. Also, the challenging issues in designing an energy harvesting MAC protocol and the possible future guidelines to improve the existing energy harvesting-based MAC protocols were not considered. Similar to the previous literature review paper [20], briefly explains the primary sources of ambient energy for energy harvesting IoT systems and the architecture of the energy harvester node. In this work, the author emphasizes the ENO condition as the main difference between the non-energy harvesting MAC protocols and energy harvesting ones. Although more energy harvesting MAC protocols have been studied in the research, the studies are still limited to a few well-known MAC mechanisms. In contrast to the presented work in [19], the open issues and future research directions to improve the energy harvesting MAC protocols are highlighted in [20]. None of these related works have considered the actual energy consumption in the existing wireless communication technologies and the available amount of energy provided by each energy harvesting technique.

The authors in [21] first examined the amount of energy produced by different energy harvesting techniques and their characteristics. Then, they highlighted the requirements of the energy harvesting IoT systems. The presented classification in this work was accomplished by reviewing the principal characteristics of the energy harvesting MAC protocols the type of data transfer start point (sender, receiver, or sink initiated). The selected MAC protocols mainly operate based on the Carrier Sensing Multiple Access (CSMA) method, where the nodes listen to the shared medium before starting the transmission, and polling approach, which benefits from a poll frame to avoid collision frames in the transmissions. Similar to the aforementioned survey papers, the advantages and disadvantages of each selected protocol are explained. Also, their performance in terms of different KPIs is highlighted. In contrast to the two aforementioned survey papers, in [21], the authors studied both ambient and non-ambient energy harvesting MAC protocols. Moreover, in those papers, approaches such as hybrid access and cross-layer, which have recently attracted more attention due to their ability to optimize network performance, were not considered.

One of the latest classifications of energy harvesting MAC protocols is proposed in [22], where in addition to sender/receiver-initiated divisions are used by the aforementioned survey papers, approaches such as scheduled-based access protocols are included in this classification. Then, some energy harvesting MAC protocols' functionality is explained based on the MAC layer requirements in IoT systems. Although this work includes a much more comprehensive number of energy harvesting MAC mechanisms than the previous surveys, the authors do not provide any information regarding the harvesters' available energy, which is required to optimize the MAC layer operations.

Alongside the energy harvesting MAC protocol categorizations, some studies focus on a specific group or features of the IoT systems MAC protocols and then explain the available energy harvesting MAC protocol within the selected group. For instance [23,24], emphasized the importance of the Wake-Up Radio (WUR) concept in reducing the energy consumption of the IoT systems and studied the available WUR MAC protocols. Since the focus of these papers is WUR, no information is provided about the issues that arise with enabling energy harvesting techniques at MAC protocols. Another example that is presented in [25] classifies the MAC protocols in IoT systems based on a specific feature of these protocols and analyzes the MAC protocols operations regarding the selected feature. In this work, the authors consider wake-up/idle scheduling duration. Then, they explain the functionality of the most well-known energy harvesting MAC protocols within this classification, along with battery characteristics and conditions in IoT systems. Although this work provides a deep understanding of the MAC functionality that operates based on the wake-up/idle scheduling approach, there are other existing energy harvesting MAC protocols that cannot be explained through this classification. The authors in [25] accomplished a deep analysis of the estimation of the remaining energy in the batteries of wireless communication devices by presenting energy models of these batteries. However, the amount of available energy provided by different energy harvesters and actual energy consumption models based on various existing wireless communication technologies was not considered.

To the best of our knowledge, in the available state-of-the-art, the importance of the required amount of energy for the communication unit and the compatibility of the selected energy harvesting MAC protocols with the potential wireless communication technologies are not investigated. Also, the existing literature lacks a complete and sound classification covering all the most relevant existing energy harvesting MAC protocols in the literature, where not only the conventional approaches are studied, but also recent novel approaches are considered. Thus, in this survey paper, we fill this gap in the literature by investigating the mechanisms of the most relevant energy harvesting MAC protocols along with their benefits and drawbacks. Specifically, we first present a categorization for energy-aware MAC protocols based on the adopted channel access method. We also provide the actual amount of energy consumption in existing wireless communication technologies by providing a unified MAC-based approach. Finally, we study the available ambient and non-ambient energy harvesters in detail and investigate their compatibility with the existing wireless communication technologies.

3. Categorization of Energy-Aware MAC Protocols for IoT Systems

According to the IoT protocol stack, the MAC layer is a sub-layer of the data link layer and is responsible for scheduling transmission or possible re-transmissions over the shared medium. In wireless communication technologies of IoT systems, MAC layer operations that provide adaptive channel access may face different problems such as collisions and idle listening (mostly in random access), or synchronization and unused idle slot (in scheduled access), which consume a significant portion of available energy of the IoT systems. Besides requiring different energy levels for MAC layer performance, wireless communication technologies are kept powered by conventional batteries. However due to the technological limitations of batteries, they may not perform for a long duration. Although the lifespan of the batteries can be increased by deploying energy harvesting technologies, due to the erratic and unpredictable nature of the provided energy, conventional MAC layer mechanisms are not compatible with these technologies. Thus they need modifications to integrate with energy harvesting techniques [21]. Since this paper focuses on the energy harvesting MAC protocols for IoT systems, this section describes how each MAC operates, together with the limitations of existing MAC protocols. These limitations can be understood with the help of a comprehensive categorization of energy-aware MAC protocols based on the performance and features of the protocols. Later in the document, Section 6 details how energy harvesting technologies are integrated within each energy-aware MAC protocol. This section provides an energy-aware MAC protocols categorization (cf. Figure 3).

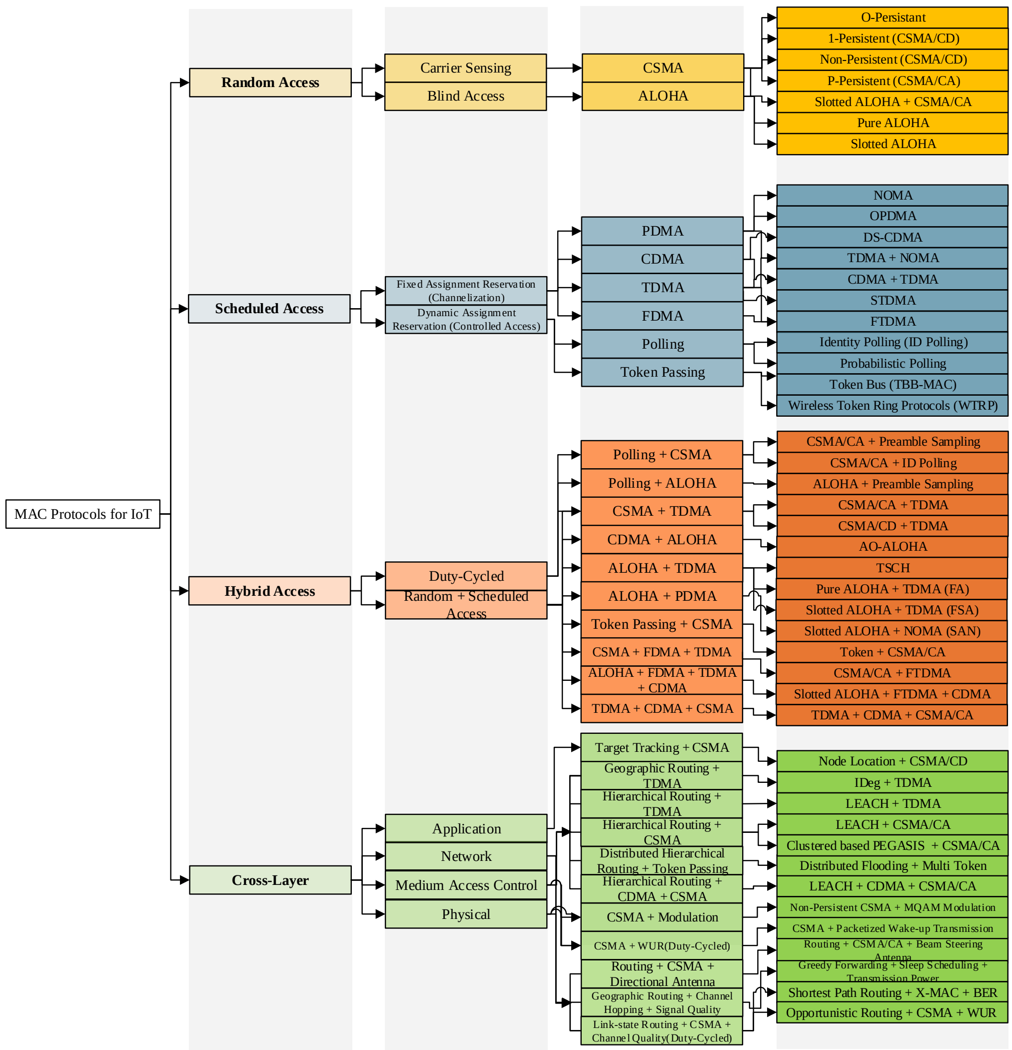


Figure 3. IoT systems Medium Access Control categorization.

3.1. Random Access

In this category, there is no coordinator to schedule the transmissions, and each node independently starts the transmission at any time. This category is divided into two subcategories: carrier sensing, blind access. Readers interested in further details of the random access category described in this subsection are referred to [26–28].

3.1.1. Carrier Sensing

In the carrier sensing procedure, each node can sense the carrier signal of the other nodes of the network and decide whether to start the transmission or wait.

Carrier Sensing Multiple Access (CSMA): This sensing procedure is performed based on 1-Persistent and Non-Persistent, which are used in CSMA with Collision Detection (CSMA/CD) systems, or P-Persistent mechanism, which is used in CSMA with Collision Avoidance (CSMA/CA). In O-Persistent a supervisor updates the order of transmission for each node based on the ongoing transmissions.

3.1.2. Blind Access

Since in this subcategory, the transmission procedure starts without sensing the shared medium, the probability of collision, and consequently, the energy consumption of the transmission procedure is higher than in the CSMA method.

ALOHA: This method is divided into Pure ALOHA and Slotted ALOHA mechanisms. Due to the slot definition in the Slotted ALOHA structure, the frame transmissions in the Slotted ALOHA mechanism are more energy-efficient from the end node perspective than the Pure ALOHA.

3.1.3. Combination of Carrier Sensing and Blind Access

CSMA + ALOHA: This mechanism adds the collision avoidance feature of CSMA/CA to reduce the probability of frame collisions (Slotted ALOHA + CSMA/CA) and consequently reduce the wasted energy of re-transmitted frames.

3.2. Scheduled Access

Frame transmission in the scheduled access category occurs in a an organized manner, where all the nodes start transmissions at predefined slots or are controlled by a coordinator. Readers interested in further details of the scheduled access category described in this subsection are referred to [26,29].

3.2.1. Fixed Assignment Reservation (Channelization)

In this subcategory, the shared medium is divided into a fixed amount of channel resources (slots of time/frequency/power/spread spectrum). Each node is only allowed to use the slots allocated to it and therefore does not contend to access the shared medium.

1. Code Division Multiple Access (CDMA): Before initiating the transmission, different codes are assigned to the nodes to encode their data.The most widely used mechanism of this method is Direct-Sequence CDMA (DS-CDMA), which reduces the total energy consumption of the network by using wide band signals with randomness that have lower interference compared to narrow band signals.
2. Time Division Multiple Access (TDMA): This method divides time into several periods, which itself is divided into a certain number of time slots. An advanced mechanism based on the TDMA method is Spatial Time Division Multiple Access (STDMA) that can reduce the energy consumption of the nodes by re-assigning time slots based on geographical locations/space, where the number of the unused slots is reduced by deactivating a certain number of slots which can save energy.
3. Frequency Division Multiple Access (FDMA): This method divides the medium into different frequencies, which are then assigned separately to each node. Since FDMA mechanisms such as Orthogonal FDMA (OFDMA) are non-energy efficient, it is out of scope in our current evaluation.
4. Power Division Multiple Access (PDMA): To share the power of the channel between nodes and avoid collisions, PDMA allocates specific transmission power to each node. The Non-Orthogonal Multiple Access (NOMA) intends to simplify the power

division procedure while satisfying the QoS requirement of the transmission, co-channel interference cancellation, fairness improvement, and simultaneous successful frame reception [30]. The Orthogonal Power Division Multiple Access (OPDMA) [31] reduces the required energy for defining and assigning power slots to each node, and consequently, it decreases the network energy consumption.

3.2.2. Combination of Channelization Methods

This subcategory combines the features of different channelization methods to improve energy efficiency, which leads to a more efficient resource allocation, transmission coordination, and more flexibility in terms of the traffic type and network size.

1. TDMA + PDMA: In this mechanism, nodes are divided into groups, and then a time slot is assigned to each group of nodes. Thus, the nodes within each group can start the transmission simultaneously [32].
2. TDMA + CDMA: In this method, time slots are assigned to different nodes which communicate through CDMA.With this combination, fewer time slots are required to have a successful frame transmission, which improves the performance of the network in terms of energy efficiency, flexibility, and scalability [33].
3. TDMA + FDMA: This mechanism, also called Frequency Time Division Multiple Access (FTDMA), in which, before initiating/allowing transmission, each node is assigned a specific time slot and appropriate frequency by the coordinator [34]. Thus, FTDMA reduces the number of the frame re-transmission which in return decreases the consumed energy of the network.

3.2.3. Dynamic Assignment Reservation (Controlled Access)

In the dynamic assignment subcategory, coordination is achieved by a control message (poll, token), and only one node can start the transmission at a particular time.

1. Token passing: This method is divided into two mechanisms, Token Bus [35], where the token frame is passed in a probabilistic manner among a group of nodes enclosed in an area, and Wireless Token Ring Protocol (WTRP) [36], in which the nodes create a ring that token frame can pass through it only in one direction.
2. Polling: This method is divided into two mechanisms, Identity Polling (ID Polling) [37] and Probabilistic Polling [38]. In the first mechanism, a specific ID is assigned to each node. If the polling packet contains their ID, they start the transmission. If not, they have to wait for their turn. In the second mechanism, the polling packet contains the contention probability, which the coordinator assigns and allows each node to start the transmission according to a probability.

3.3. Hybrid Access

This category combines the benefits of the random (i.e., distributed nature, full channel utilization) and the scheduled access (i.e., contention-free for long frames) categories while diminishing their drawbacks. This category is divided into two subcategories: combination of random access and scheduled access, and duty-cycled.

3.3.1. Combination of Random and Scheduled Access

A coordinator node schedules the timing for starting a random access-based data frame transmission. Thus, this method adapts to the network traffic conditions swiftly, optimizes the channel access method, and subsequently reduces the energy consumption of the network. Moreover, the mechanisms in the hybrid access category can guarantee the QoS, delay, and frame collision rate reduction. However, this strength in hybrid access may increase the level of MAC mechanisms complexity.

1. CDMA + ALOHA: The orthogonality feature of CDMA Slotted ALOHA [39] mechanism, makes the simultaneous transmissions possible with more efficient use of network resources and prevents degradation in the network's performance.

2. ALOHA + TDMA: This combination is divided into three mechanisms, which are known as Frame ALOHA (FA), Frame Slotted ALOHA (FSA) [40], and Time Slotted Channel Hopping (TSCH) [41]. In these mechanisms, thanks to the contention-free feature of the TDMA, the number of frame re-transmission is reduced, and thus, the available energy of each node is conserved.
3. CSMA + TDMA: This combination includes CSMA/CA + TDMA [42–44], and CSMA/CD + TDMA [45] mechanisms. In these mechanisms, the reservation slot nature of TDMA provides a contention-free transmission for the mechanisms based on the random access category to avoid collision problems.
4. ALOHA + NOMA: One such mechanisms is the Slotted ALOHA-NOMA (SAN) [46] mechanism, which adds the MU feature of the NOMA to the slotted ALOHA mechanism to enhance the performance in terms of energy efficiency, low complexity, ease of implementation, and improved scalability.
5. Polling + CSMA: One of the mechanisms of this method is ID Polling + CSMA/CA [47], in which the coordinator defines the ID Polling period for each node by sending a specific polling frame to each node and then, each node only wakes up if it has a frame to send and transmits the frame based on the CSMA/CA mechanism.
6. Token passing + CSMA: A mechanism based on this method is known as Token + CSMA/CA [48,49], which is introduced as a multi-token-based approach with a random sleep scheduling structure.In this mechanism, several coordinators are defined to manage the transmissions based on their token frames.
7. CSMA + FDMA + TDMA: In CSMA/CA + FTDMA [50], the contention-free feature of both TDMA and FDMA is combined to conserve the energy, and the RTS/CTS handshaking method of CSMA/CA to reduce the hidden terminal issue.
8. ALOHA + FDMA + TDMA + CDMA: An example of this method is the Slotted ALOHA + FTDMA + CDMA [51], in which a coordinator node broadcasts time, frequency, and code slots to the nodes of the network. Then, each node randomly chooses a set of slots and is only allowed to start the frame transmission at these reserved slots. This pre-assignment of FTDMA and CDMA reduces collision probability and thus results in some energy saving at the node.
9. TDMA + CDMA + CSMA: In TDMA + CDMA + CSMA/CA [52] mechanism, the nodes are located inside the cluster (inter-cluster) and transmit short frames. In this mechanism, transmission power and times are controlled for each node; thus, the IoT systems' energy efficiency is improved.

3.3.2. Duty-Cycled

This subcategory is one of the main techniques to conserve transmission energy in IoT systems by adjusting the active and sleep duration of each node.

1. CSMA + Polling: This mechanism's main target is to recognize the receiver, reduce the idle listening duration, and consequently reduce the total energy consumption of the network. This goal is achieved by applying a preamble sampling or preamble strobing approach, where each node transmits a low power preamble frame to announce the access point that it intends to start the transmission [25].
2. ALOHA + Polling: In this mechanism, the sender starts the transmission only a short duration before the receiver's wake-up time based on the ALOHA method. Thus, the long preambles are reduced to shorter ones, which helps reduce the energy consumption of the network.
3. CSMA + TDMA: In this method, the data transmission procedure is started precisely after the receiver wakes up, making the listening duration shorter than previous approaches. Thus less energy is consumed during the listening period [25].

3.4. Cross-Layer

Since the network peripherals could be better managed by understanding the dynamics of each IoT protocol stack's layer, in this category, two or three layers of the IoT protocol stack interact with each other simultaneously to optimize the performance of the network, especially in terms of energy consumption.

3.4.1. Interaction between Application and MAC Layers

In this subcategory, the MAC layer interacts and exchanges information with the application layer to improve its mechanism. For instance, the application layer information, such as the QoS requirements or the application sensitivity to the network performance, can optimize the transmission scheduling process at the MAC layer.

Target tracking + CSMA: In a monitoring area, predicting the next location of a mobile node is known as target tracking, which is mostly done by its neighboring nodes. In this subcategory, the total energy consumption of the network is decreased by increasing the accuracy of the position estimation of the mobile node while sending some of its neighbors into sleep mode [53]. An example of this category is Node Location + CSMA/CD [54] mechanism, which intends to balance the trade-off between the QoS improvement and the network energy consumption.

3.4.2. Interaction between Routing and MAC Layer

Since routing algorithms consume a considerable amount of energy, the interaction of an energy-efficient routing protocol with the MAC layer can improve network efficiency.

1. Geographic routing + TDMA: In this method, the geographic routing protocol generates the routing table based on the locations of the nodes. In IDeg-Routing + TDMA [55] mechanism, time slot assignments and routing tree generation occur simultaneously. Then based on the number of the routes to the same destination node, they are divided into single path or multipath scenarios. In multipath scenarios, the collision-free nature of the TDMA method and selecting the route with the highest amount of residual energy reduces the network energy consumption.
2. Hierarchical routing + TDMA: To reduce the energy consumption of the network and expand its lifetime, the Low Energy Adaptive Clustering Hierarchy (LEACH) routing approach is adopted in LEACH + TDMA [56] method, in which the network is divided into several clusters. Each cluster head is selected randomly and based on the remaining energy of the node and its distance to the base station.
3. Hierarchical routing + CSMA: This method includes two mechanisms, LEACH + CSMA/CA [57] and Power Efficient Gathering in Sensor Information Systems (PEGASIS) + CSMA/CA [58]. In the first mechanism, due to the sleep duration added to the CSMA/CA , the energy consumption of the nodes in LEACH + CSMA/CA is lower than LEACH + TDMA. In the PEGASIS mechanism, to reduce the energy consumption of the network, all the nodes go to the sleep state unless they have a frame to send or if they are going to receive a frame.
4. Distributed hierarchical routing + Token passing: One example of this method is an energy-efficient cluster-based routing protocol that interacts with a token passing method. The target of Distributed Flooding + Multi Token [59] mechanism is that the network continues to operate even if some nodes are disconnected from the network and conserve the network energy consumption.
5. Hierarchical routing + CDMA + CSMA: An example of this method is LEACH + CDMA + CSMA/CA [60,61], in which the inter-cluster nodes are assigned to a certain number of time slots based on their available energy levels, which can schedule the sleep state duration of each node. For these reasons, some part of the energy budget of the network is saved, and the network lifetime is expanded.

3.4.3. Interaction between MAC and Physical Layers

In this method, several parameters of the physical layer, such as power and sub-carrier allocation strategies, antenna cooperation, and beam-forming techniques, are used to enable the energy-efficient scheduling transmission in the MAC layer.

1. CSMA + Modulation: An example of this method is an interaction of an adaptive modulation with a multi-channel CSMA, known as CSMA + M-Ary Quadrature Amplitude Modulation (MQAM) [62]. In this mechanism, the modulation scheme information, along with an adaptive back-off probability, can reduce the delays due to the re-transmissions and thus save the energy budget of the network.
2. CSMA + WUR: This method proposes a CSMA-based mechanism with two different approaches for ultra-low power networks. The first one reduces the energy consumption due to the overhearing issue by continuously packetizing the wake-up transmissions. The second one operates based on the energy existence on the channel and reduces the size of the receive check [63].

3.4.4. Interaction between Routing, MAC and Physical Layers

In this method, the routing and physical layer innovations can assist the MAC layer to operate in an energy-efficient manner [64].

1. Routing + CSMA + Directional antenna: An example of this method is Routing + CSMA/CA + Beam Steering Antenna [65], in which to conserve the energy budget of the network, the CSMA method adjusts the wake-up/sleep scheduling duration of the radio transceiver to the traffic load adaptively and makes the transmissions more energy-efficient. This mechanism benefits from the advantages of directional antennas (where the antenna only radiates in a narrower geographical area), making simultaneous transmissions possible.
2. Geographic routing + Channel hopping + Signal quality: A mechanism that belongs to this method is Greedy Forwarding + Sleep Scheduling + Power Transmission [66,67], in which according to the information that is provided by the routing protocol and the amount of transmission power, the MAC layer decides the sleep duration of each node; thus, it can reduce the network energy consumption.
3. Link-State routing + CSMA + Channel quality: The (Shortest Path Routing + CSMA + BER) [68] is an example of this method, which reduces the energy consumption of the network through an estimation of the Bit Error Rate (BER) and updating the information from the network layer (distance table) along with the short adaptive duration of sleep mode.

   The last mechanism refers to the interaction of a duty-cycled-based method and an opportunistic routing protocol. This mechanism applies different estimation techniques such as the Expected Duty Cycled Wakeups (EDC) and Energy-Centric Data Collection with Anycast in Duty-Cycled (EDAD). It uses the information provided from opportunistic routing protocols to approximate the number of required wake-ups for transmitting a data frame. For this reason, this mechanism schedules the idle listening and wake-ups more precisely and thus reduces the energy consumption of the network [69–71].

4. IoT Technologies and Energy Models

In recent years, IoT communication technologies connect new approaches and concepts to meet energy efficiency requirements. In order to define the IoT requirements in terms of energy efficiency, available tools like energy models or empirical energy measurements have been used in the literature.

This section first summarizes each IoT communication technology regarding its available MAC layers and energy consumption characteristics. The available energy models in the literature are then presented and categorized based on their wireless communication technologies. In the end, this section is summarized by providing a comparison of wireless communication technologies and reviewing their applicability for IoT systems in terms of energy consumption. For this reason, the total power consumption of each technology is modeled based on the different states of its MAC layer. The parameters from the equations used in the energy consumption analyses for IoT technologies are explained in Table 1.

Table 1. Parameters of the energy model equations.

Parameter	Description
E_{Total}	Total energy consumption
E_{Sl}	Energy consumption in sleep mode
E_{Wu}	Energy consumption of wake-up mode
E_{m}	Energy consumption during data measurement
E_{Mcu}	Energy consumption of microcontroller processing
E_{Wut}	Energy consumption of wake-up mode for transceiver
E_{Tx}	Energy consumption of transmission mode
E_{Rx}	Energy consumption of reception mode
E_{Ifs}	Energy consumption during the inter-frame space
E_{Id}	Energy consumption of idle mode
E_{Disconn}	Energy consumption of User Equipment(UE) disconnected mode
T_{Tx}	Duration of transmission mode
T_{Rx}	Duration of reception mode
T_{Id}	Duration of idle mode
T_{Sl}	Duration of sleep mode
T_{Wu}	Duration of wake-up mode
T_{Cd}	Duration of cool down mode
T_{Sw}	Duration of switching mode from transmission to reception and vice versa
P_{Tx}	Power consumption of transmission mode
P_{Rx}	Power consumption of reception mode
P_{Id}	Power consumption of idle mode
P_{Sl}	Power consumption of sleep mode
P_{Wu}	Power consumption of wake up mode
P_{Cd}	Power consumption of cool down mode
P_{Sw}	Power consumption of switching mode from transmission to reception and vice versa
n	Number of the tag

4.1. Wireless Local Area Network (WLAN)

The Institute of Electrical and Electronics Engineers (IEEE) 802.11 technology was designed based on a random access mechanism (CSMA/CA), which is an energy-consuming protocol [72]. The reason for that is the collision avoidance functionality of this protocol, which keeps stations awake (in active mode) to listen to the channel for a certain duration before attempting to transmit [73]. To cater to this drawback, a power management mode was introduced to IEEE 802.11 standard [74]. In this technology, the total energy consumption is obtained through the consumed energy within the different states of the communication, where the consumed energy of each state is the multiplication of the power consumption of that state to its corresponding duration. The energy consumption model for IEEE 802.11 technology is obtained through Equation (1), defined in [75].

$$E_{\mathrm{Total}} = T_{\mathrm{Rx}}.P_{\mathrm{Rx}} + T_{\mathrm{Tx}}.P_{\mathrm{Tx}} + T_{\mathrm{Id}}.P_{\mathrm{Id}} + T_{\mathrm{Sl}}.P_{\mathrm{Sl}} \quad (1)$$

The IEEE 802.11 standard group has introduced in recent years different amendments that aim to satisfy the IoT systems requirements. Within these amendments, the original channel access method has been changing through the technical definition of each amendment, looking for better performance in IoT systems. Below, the most relevant energy models for the IoT-compatible IEEE 802.11 amendments are described.

4.1.1. IEEE 802.11ah

Similar to the legacy IEEE 802.11, the channel access method of IEEE 802.11ah is based on CSMA/CA. However, additional features to the MAC layer such as hierarchical Association IDentifiers (AID), group sectorization, Restricted Access Window (RAW), Relay Access Point (Relay AP), bi-directional Transmission Opportunity (TXOP), and Target Wake Time (TWT) [76], make IEEE 802.11ah acceptable for IoT systems with a large number of devices deployment (by reducing the contention), and low power communications. Due to the equality of the channel access method of this amendment and IEEE 802.11 standard, the total energy consumption of this technology is also obtained through Equation (1). The IEEE 802.11ah energy model was first introduced by Raeesi et al. [77], where the sleep duration is extended, and power consumption of transmission state is reduced by utilizing short beacon frames, short MAC header, etc. Thus, the total energy consumption is reduced. This energy model was later reformulated by Bel et al. [78] to consider TIM and page segmentation scheme.

Along with the analytical models, empirical power consumption analyses have been performed based on real hardware measurements included in the Orinoco Wireless Fidelity (WiFi) card data sheet [79] and smart grid IEEE 802.11ah chip designed in [80]. The analytical models do not consider the energy consumption of hardware components such as the microcontroller, whereas energy models based on real measurements do so.

4.1.2. IEEE 802.11ax

The channel access method of this technology adds OFDMA on top of CSMA/CA.A MAC feature that makes IEEE 802.11ax a suitable technology for dense environments is the Basic Service Set (BSS) coloring [81]. Moreover, in this technology, energy efficiency can also be achieved through approaches such as microsleep, TWT, and Opportunistic Power Save (OPS) [82].

According to the channel access mechanism of IEEE 802.11ax technology, the energy model of this technology includes the basic four states of Equation (1). An OFDMA-based Hybrid Channel Access (OHCA) for uplink MU transmissions is introduced in [83], and an energy model based on the MU power-saving mode is proposed in [84]. Through this model, the authors showed that, by defining a certain sleep duration for the uplink flow, it is possible to save a significant amount of power. The total energy consumption for the power saving mode is obtained through Equation (2).

$$E_{\text{Total}} = T_{\text{Rx}}.P_{\text{Rx}} + T_{\text{Tx}}.P_{\text{Tx}} + T_{\text{Sl}}.P_{\text{Sl}} \tag{2}$$

According to Equation (2), for uplink transmissions, the station only wakes up from deep sleep mode when it wants to receive or transmit frames. Thus, in power saving mode, the idle mode is removed from the total energy consumption Equation (1).

4.1.3. IEEE 802.11ba

This amendment aims to balance the trade-off between low latency and low power states (1mW) in devices [85–87] while being backward compatible [88]. This amendment works on WUR, whose implementation is based on a Wake-up Transmitter (WuTx) and Wake-up Receiver (WuRx). Since the WuRx is a very low power consumption radio and the primary radio wakes up on-demand, the power consumption during idle mode decreases significantly [88].

The channel access method IEEE 802.11ba is the Enhanced Distributed Channel Access (EDCA) based on CSMA/CA, and power-saving mode is fulfilled through the WUR. The total energy consumption of IEEE 802.11ba is modeled in [89], where a dynamic hybrid WLAN communication model for IoT devices is considered. In this model, MU operation (IEEE 802.11ax) and WUR (IEEE 802.11ba) are taken into account. According to the proposed model presented in [89], the total energy consumption in each station is achieved through Equation (3).

$$E_{\text{Total}} = T_{\text{Rx}}.P_{\text{Rx}} + T_{\text{Tx}}.P_{\text{Tx}} + T_{\text{Id}}.P_{\text{Id}} + T_{\text{Wu}}.P_{\text{Wu}} + 2T_{\text{Sw}}.P_{\text{Sw}} \quad (3)$$

Presenting an efficient scheme for the wake-up receiver, while considering the coexistence with IEEE 802.11 legacy, is becoming an attractive topic [88,90–93], where some of these energy models are proposed based on the AS3933 chip by Austria Microsystems.

4.2. Low-Power Wide Area Network (LPWAN)

Unlike the above IEEE 802.11 amendments, LPWAN technologies support longer communications with extremely low bandwidth, low power consumption, and constrained duty-cycles (how frequently an end-device transmits data) [94]. These features make LPWAN technologies more attractive for IoT than other long-range communication technologies. Long-Range Wide Area Networks (LoRaWAN), Sigfox, and Narrow-Band IoT (NB-IoT) are described next as LPWAN examples.

4.2.1. LoRa

The basic channel access method is a simple random channel access mechanism (Pure ALOHA/Slotted ALOHA), which simplifies this technology at the protocol level [95]. However, to reduce the power consumption in long-range communication, the MAC layer of this technology has been modified by adding sleep mode (CSMA feature) at its protocol level [96,97].

To the best of our knowledge, the basic energy models for LoRa technology are designed based on the real Class A device characteristics to the date of this paper. An energy consumption analysis and its model design for the most common LoRa transceiver chip, SX1272, are presented in [98,99]. The accuracy of the proposed energy model, which mimics the energy consumption of the LoRaWAN Class A device, is evaluated through simulation in Network Simulator-3 (NS-3) [99]. Thus the total energy consumption of a simple data transmission procedure can be derived from Equation (4).

$$E_{\text{Total}} = T_{\text{Rx}}.P_{\text{Rx}} + T_{\text{Tx}}.P_{\text{Tx}} + T_{\text{Sl}}.P_{\text{Sl}} \quad (4)$$

An energy consumption estimation based on the different states of the LoRaWAN hardware is proposed in [100] through Equation (5). Since this model is formulated based on a real sensor node, some parameters such as a wake-up transceiver, microcontroller, and data measurement are added to Equation (4). According to the authors, this model is applicable for Class A end devices.

$$E_{\text{Total}} = E_{\text{Rx}} + E_{\text{Tx}} + E_{\text{Sl}} + E_{\text{Wu}} + E_{\text{m}} + E_{\text{Mcu}} + E_{\text{Wut}} \quad (5)$$

4.2.2. Sigfox

The channel access method in Sigfox is known as Random Frequency and Time Division Multiple Access (RFTDMA). To provide a simple and low power consumption at the protocol level, this technology limits the number of data transmissions [101] and does not use packet synchronization and beacon frames [72].

According to the authors in [102], the total energy consumption of a bidirectional Sigfox-based communication for the MKRFOX1200 device can be modeled based on the different states of the transaction, which includes wake-up, transmission, listening, reception, cool down, and sleep states. According to this model, the total energy consumption of a MKRFOX1200 device is obtained through Equation (6).

$$E_{\text{Total}} = T_{\text{Wu}}.P_{\text{Wu}} + T_{\text{Rx}}.P_{\text{Rx}} + 3.T_{\text{Tx}}.P_{\text{Tx}} + 2.T_{\text{Id}}.P_{\text{Id}} + T_{\text{Cd}}.P_{\text{Cd}} + T_{\text{Sl}}.P_{\text{Sl}} \quad (6)$$

Moreover, in [102] an analytical model for energy consumption of data delivery and battery lifetime of the MKRFOX1200 Sigfox device is proposed. The novelty of this work is the impact consideration of the frame losses.

4.2.3. NB-IoT

This technology reduces the power consumption by using different power saving mechanisms such as Handling Re-transmission (HARQ), Extended Discontinuous Reception (eDRx), and Wake-up (Wu) signal. The eDRx reduces the power consumption by keeping the device in an inactive mode for a long duration (deep sleep mode), whereas Wu signal is sent during the idle mode to wake-up the main receiver [103].

Although in NB-IoT technology, different channel access methods are deployed for uplink and downlink communications (SC-FDMA, OFDMA), a single energy model is valid for both uplink and downlink communications, where the energy consumption of transmission mode can be defined as an uplink or downlink flow. This model is defined in [104], where four different communication modes (wake-up and connect, transmission, disconnect and sleep/idle) are considered. Equation (7) expresses the total energy consumption of this technology.

$$E_{\mathrm{Total}} = E_{\mathrm{Wu}} + E_{\mathrm{Tx}} + E_{\mathrm{Disconn}} + E_{\mathrm{Id}} \tag{7}$$

In the work presented by [105], two different methods are defined for each communication flow. In this model, the authors utilized power-saving mode for uplink and eDRX mechanism for downlink communications (sleep/idle mode extension) to reduce the total energy consumption. The authors showed that their proposed energy model is able to prolong the battery life over 12 years.

4.3. Radio Frequency Identification (RFID)

Compared to the LPWAN technologies, which provide long-range communication, RFID and Near-Field Communication (NFC) are suitable for shorter-range applications.

The high-level classification of RFID technology divides it into passive and active.

Passive technology tags are kept powered through a passive technique such as energy harvesting methods or backscattering. One of these technologies is the Electronic Product Code Class 1 Generation 2 (EPC Gen2) [106]. Passive tags are small, cheap, and ultra-low power consumption, these features making them suitable for massive deployment environments and hard to reach use cases. However, this technology suffers from a low communication range (10 m) [107].

Active technology refers to the devices that require power supply on tags such as a battery. This technology is not as popular as passive RFID. The active technology can transmit stronger signals and, in consequence, provide a more extended range of communication (100 m) [108]. However, compared to passive tags, they are large and expensive (due to their on-board batteries).

Due to the random nature of the channel access method in this technology (Slotted ALOHA or FSA), transmission and reception states are considered to define the energy model. The proposed energy model in [109] is based on an energy-aware ALOHA channel access, where the consumed energy per tag is obtained through Equation (8).

$$E_{\mathrm{Total}}/n = E_{\mathrm{Rx}}/n + E_{\mathrm{Tx}}/n \tag{8}$$

4.4. Wireless Personal Area Network (WPAN)

In contrast to the above wireless technologies, the WPAN technologies are applicable only for personal network applicationswhere short-range and low power consumption communications are required. Among WPAN technologies, Bluetooth Low Energy (BLE-Bluetooth 4.0) and Zigbee (IEEE 802.15.4) are the most energy-efficient and cost-effective ones. Thus, they are the most adopted WPAN standards for IoT use cases [110].

4.4.1. BLE

The BLE-based device is always in sleep mode and wakes up only for short periods based on its channel access method (TDMA). This wake-up period is called connection state [72]. Based on the proposed energy model in [111], during these periodic wake-up intervals, a short delay is defined as the Interframe space (Ifs). This delay is the time interval between transmission and reception in each connection. The total energy consumption of the slave connection is expressed through Equation (9).

$$E_{\text{Total}} = E_{\text{Wu}} + E_{\text{Rx}} + E_{\text{Tx}} + E_{\text{Ifs}} + E_{\text{Mcu}} \quad (9)$$

The energy model presented in [111] is designed based on the BlueGiga BLE112 hardware module (based on TI's CC2540 System-On-Chip). Since this model is based on real hardware, some parameters such as energy consumption in microcontroller and Ifs are also taken into account.

4.4.2. Zigbee

Similar to the IEEE 802.11 legacy, the basic channel access method of this technology is based on the CSMA/CA mechanism [72]. Since it is a low data rate technology, devices usually stay in sleep mode and only wake up for short periods to send data, reducing power consumption. Compared to the IEEE 802.11ah/ax, Zigbee is a low complex and low power consumption (about four times less) technology, which prolongs the battery lifetime while it provides less coverage range [112].

The proposed energy model in [113] is designed based on the random nature of the channel access method, where due to the three aforementioned characteristics, the number of collisions and consequently re-transmissions are reduced. Since the channel access method in Zigbee and IEEE 802.11 standard is the same, the total energy consumption for this technology is also obtained based on Equation (1).

The aforementioned wireless communications are just a few technologies that can be considered the potential communication technologies for IoT systems. Other potential communication technologies can be listed as Z-Wave, Weightless SIG, Wireless Highway Addressable Remote Transducer (WirelessHART), THREAD, ANT+, Long Term Evolution for Machines (LTE-M), and Extended Coverage Global System for Mobile communication (EC-GSM). Readers interested in further details of different LPWAN technologies are referred to the papers [94,98].

4.5. Comparison of Communication Technologies and Their Suitability for IoT Regarding Energy Consumption

Table 2, which is built based on the references [72,76,88,114], provides a brief comparison of the technologies mentioned above in terms of the most relevant aspects regarding the IoT paradigm. Then, the IoT-related MAC features of each potential communication technology are listed in Figure 4.

Table 2. Overview of potential technologies for IoT.

Technology	Standard	Coverage Range	Data Rate (Max)	Frequency	MAC Protocol	IoT Application
WiFi HaLow	802.11ah	<1.5 km	346 Mbps	Sub-1 GHz	CSMA/CA	Smart City
WiFi-6	802.11ax	<300 m	9.607 Gbps	1–6 GHz	OFDMA	Retail Smart Transportation
WiFi-WUR	802.11ba	<50 m	0.25 Mbps	2.4/5 GHz	CSMA/CA	Smart City Smart Healthcare
LoRa	LoRaWAN	<20 km	<25 kbps	Sub-1 GHz	ALOHA	Smart City
Sigfox	Sigfox	<40 km	0.1 kbps	Sub-1 GHz	RFTDMA	Industrial Automation Smart City
RFID	EPC global Gen2	10 m	423 kbps	850/950 MHz	FSA	Supply Chain
Bluetooth	802.15.1	100 m	3 Mbps	2.4 GHz	TDMA	Smart Transportation Smart Buildings
BLE	802.15.1	100 m	1 Mbps	2.4 GHz	TDMA	Smart Healthcare
ZigBee	802.15.4	<100 m	250 kbps	2.4 GHz	CSMA/CA	Smart Buildings
Z-Wave	Z-Wave	10 m	100 kbps	Sub-1 GHz	CSMA/CA	Smart Buildings
Weightless SIG	Weightless (W/N/P)	5 km	10 Mbps	Sub-1 GHz	SA FTDMA	Smart City
WirelessHART	802.15.4	100 m	250 kbps	2.4 GHz	TDMA	Industrial Automation
NFC	ISO 13157	0.1 m	424 kbps	13.56 MHz	TSCH CDMA/CA	Retail Smart Buildings
THREAD	802.15.4	11 m	250 kbps	2.4 GHz	TSCH	Smart Buildings
ANT+	ANT+ Alliance	100 m	1 Mbps	2.4 GHz	TSCH	Smart Healthcare
NB-IoT	3 GPP	<100 km	250 kbps	Cellular Bands	OFDMA SC-FDMA	Industrial Automation Retail
LTE-M	3 GPP	<100 km	1 Gbps	Cellular Bands	OFDMA	Smart Transportation
EC-GSM	3 GPP	<100 km	2 Mbps	Cellular Bands	TDMA FDMA	Industrial Automation

For instance, in the LPWAN family, NB-IoT is a license-based standard, while LoRa and Sigfox work on the unlicensed Radio Frequency (RF) spectrum, and these technologies support communications with a long-range and low data rate. For this reason, they are mostly deployed in IoT applications such as smart cities and industrial automation. Other than LPWAN technologies, WLAN technologies benefit from the characteristics and features of the CSMA method to manage the collision frame during the transmission procedure and provide services such as QoS and QoE. For example, to support QoS, WLAN technologies support EDCA based on their MAC layer functionality, whereas this is not provided in LPWAN proprietary technologies (cf. Figure 4). In contrast to LPWAN and WLAN families, BLE technology which belongs to the WPAN family is the most widely deployed in IoT healthcare applications due to the collision-free characteristic of its MAC layer and its low power consumption communications. However, since the WPAN family is applicable for short-range transmissions, it may not be practical in IoT applications that require long-range such as smart transportation.

According to the power consumption values of the different communication states of IoT technologies (cf. Table 3), and the limitations of each wireless communication technology, some of these technologies may be more appropriate for IoT implementation.

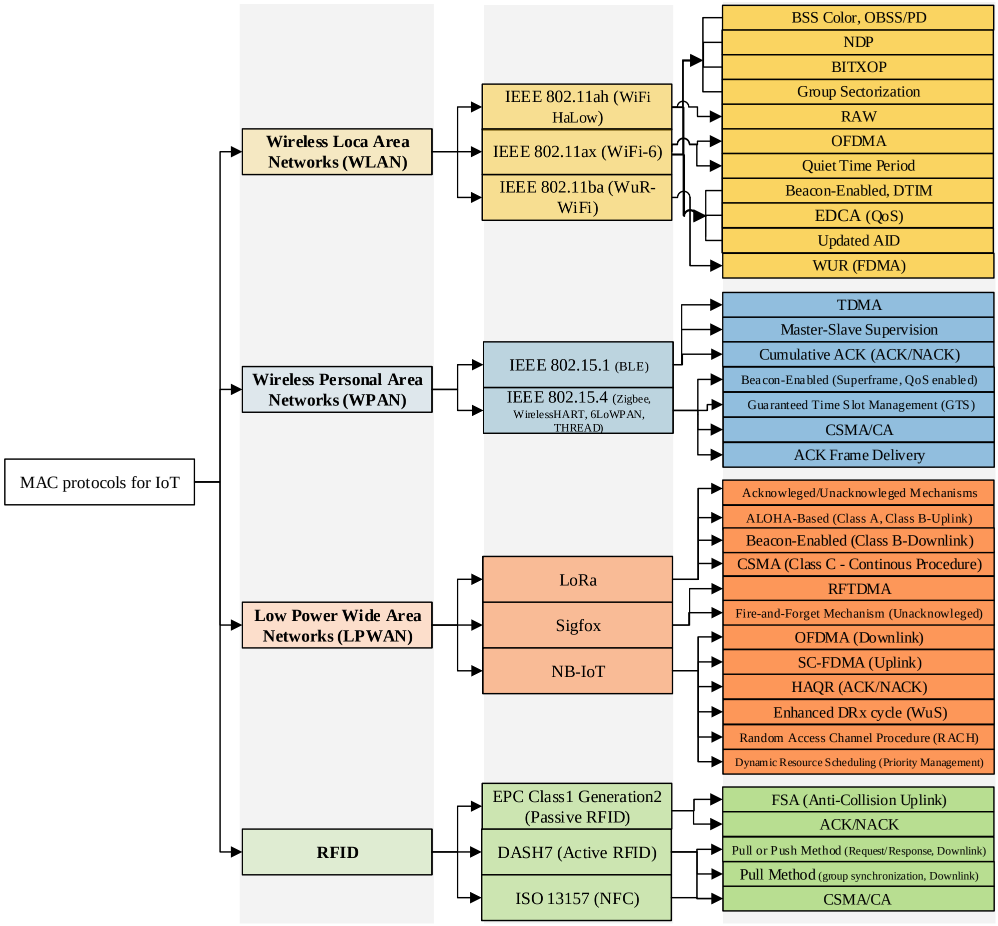


Figure 4. Overview of the MAC protocols of the current IoT technologies.

Table 3. Power consumption for IoT technologies (mW).

Wireless Standards	Tx	Rx	Idle	Sleep	Research Methodologies	References
IEEE 802.11ah	255	135	1	NA	Analytical Model (Simulation OMNeT++)	Olyaei et al. [115]
	15.8	6.2	NA	10×10^{-3}	Model Design and Creation (Matlab Simulation)	Zheng et al. [80]
	255	135	NA	1.5	Analytical Model	Raeesi et al. [77]
IEEE 802.11ax	1000	600	300	150	Model Design and Creation (computer simulations)	Yang et al. [84]
IEEE 802.11ba	280	100	50	NA	Model Design and Creation	Hong et al. [89]
	352	154	55	5×10^{-3}	Survey (IEEE Report)	McCormick [85]
LoRa (13 dBm)	18.81	31.65	NA	3.3×10^{-3}	Model Design and Creation	Finnegan et al. [99]
LoRa (13 dBm)	92.4	34.65	NA	0.0033×10^{-3}	(ns3)/Analytical Model	Finnegan et al. [98]
LoRa (7 dBm)	59.4	34.65	NA	0.0033×10^{-3}	Real Measurements	
LoRa (20 dBm)	419.6	44.06	NA	4.32×10^{-3}	Real Measurements	Morin et al. [116]
Sigfox (14 dBm)	214.5	132	1.65	16.5×10^{-3}	Real Measurement	data-sheet [117]
Sigfox (14 dBm)	147	30	NA	4.32×10^{-3}	Real Measurements	Morin et al. [116]
Sigfox Unidirectional TXN (14.5 dBm)	81.6	NA	3.6	48×10^{-3}	Model Design and Creation Real Measurements	Gomez et al. [102]
Sigfox Bidirectional TXN (14.5 dBm)	82.8	55.5	3.6	48×10^{-3}	Model Design and Creation Real Measurements	Gomez et al. [102]
RFID Active Tag	35	28	NA	NA	Model Design and Creation	Namboodiri
RFID Reader	825	125	NA	NA	Simulation	et al. [118,119]
801.15.1 (BLE)	84	66	NA	NA	Model Design and Creation Real Measurements	Siekkinen et al. [111]
	24.11	19.26	4.67	3.24×10^{-3}	Real Measurements	Morin et al. [116]
802.15.4 (ZigBee)	90	72	NA	NA	Model Design and Creation Real Measurements	Siekkinen et al. [111]
	163.74	89.66	40.56	0.165	Experiment	Gray et al. [120]
NB-IoT	852.92	178.34	21.6	0.0108×10^{-3}	Model Design and Creation (Matlab and ns3)	Sultania et al. [105]
	543	90	2.4	0.015	Model Design and Creation	Ratasuk et al. [121]

In comparison with IEEE 802.11 legacy, which is a power-hungry technology regarding IoT, IEEE 802.11ah and IEEE802.11ba have been able to reduce energy consumption (about 7.5 times for IEEE 802.11ah and 5 times for IEEE 802.11ba less than legacy) by introducing specific modifications [76,87]. Although the aim of IEEE 802.11ax is dense deployment (not exclusively for IoT), it can reduce the energy consumption of the network devices up to 1.5 times less than legacy by extending the duration of sleep mode [82]. However, since IEEE 802.11ba is still under development and IEEE802.11ax has not reached sufficient technical maturity yet, these technologies require more time to be well adapted for IoT applications. Since LPWAN technologies provide low energy consumption (about 7 times less than WLAN technologies) and very long coverage range (up to 100 km in case of NB-IoT) [122] communications compared to the above wireless technologies, these technologies include a wide range of IoT applications from smart buildings to industrial automation. However, the main drawback of LPWAN technologies is their low data rate. Although energy consumption by WPAN communications is lower than the aforementioned WLAN technologies (10 times less) [116,120], due to their frequency band (2.4 GHz), they suffer from interference, resulting in a loss of communication reliability. Thus, WPAN is only appropriate for smart home and wearable devices. Moreover, EPC Gen2 RFID [106] is one standard allowing passive communications, which is suitable for IoT applications in the supply chain system, with a limited communication range.

Based on the available state of the art on IoT wireless communication technologies, LPWAN technologies and IEEE 802.11ah are promising ones. Nevertheless, the limited battery lifetime of these technologies may represent an issue for specific IoT scenarios. For instance, those requiring high availability or low maintenance cannot afford frequent battery replacement. Hence, techniques to prolong battery lifetime, like energy harvesting, may improve different IoT applications.

5. Energy Harvesting Solutions for IoT Technologies

Energy harvesting systems are applied to the IoT paradigm to prolong the battery life time and make these systems more energy-efficient. The classification of energy harvesting mechanisms is based on their inherent characteristics such as, scalability, maintainability, ability to improve IoT devices life time, form factor, capacity, and sustainability. The energy harvesting mechanisms are fed by environmental and non-environmental energy sources. The former includes sun radiation, wind and water flows, geothermal, within others, whereas the latter refers to RF signals and mechanical forces.

In this section, first the most relevant IoT related features of energy harvesting systems are highlighted. Then, the structure and the functionality of those energy harvesting technologies are explained. In the end, an investigation of the compatibility of energy harvesters and the aforementioned wireless technologies is provided.

5.1. IoT Energy Source Characteristics

One of the main difficulties that IoT systems face is the limited sources of energy to keep devices powered, which is traditionally provided by batteries. Since IoT systems include thousands of devices, frequent replacement of their batteries or finding the failed ones, require time and human intervention, which increase the cost of maintenance. This issue becomes worse when the devices are located in hard-to-reach areas or mobile locations. The above battery shortcomings as energy source for IoT systems, bring energy harvesting technologies into consideration.

To continuously keep IoT systems powered, energy harvesting technologies harvest energy from the surrounding environment, which may provide longer lifetime and lower maintenance operations. Additionally, most of the energy sources in energy harvesting technologies can provide the required power for wireless communications, which makes these technologies scalable to various IoT applications and services. In contrast to battery disposal, which has negative effects to the environment [123], energy harvesting technologies can alleviate these harmful effects and move towards sustainable IoT systems. The above advantages of energy harvesting technologies over batteries can make IoT systems more feasible and cost-effective.

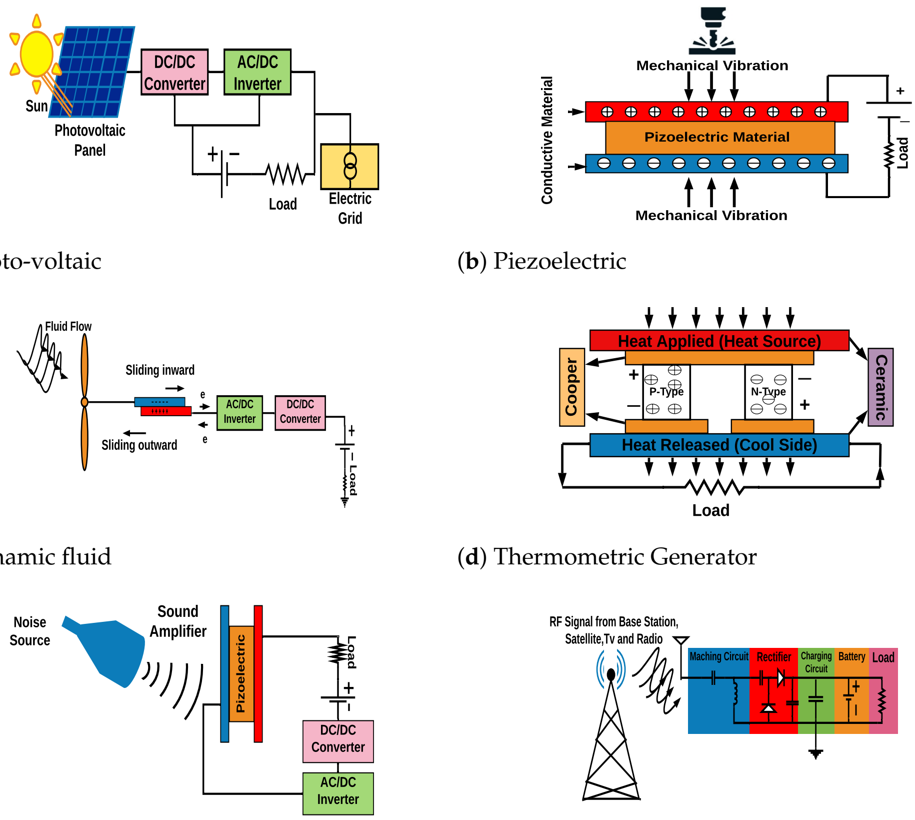
Table 4 highlights the characteristics of the main energy sources that feed harvesting systems. The main energy harvesting techniques for IoT systems are described next.

Table 4. Energy source characteristics.

Energy Source	Form Factor	Life Time	Cost	Maintenance	Reliability	Scalability	Proper Environment
Sun radiation	Medium	High	Medium	Medium	Low	Low	Outdoor
Mechanical force	Low	Low/ Medium	Medium /High	High	Medium	High	Indoor/ Outdoor
Dynamic fluid	High	High	High	Low	Low/ Medium	Low	Outdoor
Thermoelectric	High	Medium	High	Low	High	High	Industrial area
Acoustic noise	Low	Low	Medium /High	High	Medium	Low	Airport/ Railroad
RF	Medium	High	Medium	Low	High	High	Urban area

5.2. Suitable Energy Harvesting Technologies for IoT

In this section, we briefly highlight the suitable energy harvesting techniques that can be utilized in IoT devices. These methods can be fed by ambient or non-ambient sources. The illustration of each mechanism is shown in Figure 5.



(**a**) Photo-voltaic (**b**) Piezoelectric

(**c**) Dynamic fluid (**d**) Thermometric Generator

(**e**) Acoustic noise (**f**) Radio Frequency

Figure 5. Existing energy harvesting mechanisms according to their source of energy.

5.2.1. Solar-Based Energy Harvester

The high power density feature of the solar cell, makes it a suitable power unit technique for IoT applications such as smart agriculture and smart city. The solar or photo-voltaic cells absorb the energy from a natural or artificial source of light (sun or fluorescent light), and then convert it to electric current. The converted energy is conducted into two metals in the top and bottom of the cell, and is usually stored in a super-capacitor or a battery to keep IoT devices [124] powered. Based on the type of the source of light, solar cells can be indoor or outdoor, which vary in size. These cells can be as large as a solar panel (integrated cell) or a small thin-film (Dye-Sensitized). Depending on the amount of solar or fluorescent light radiation, the power density varies from 10 μW/cm^3 to 100 mW/cm^3 [125,126]. However, due to the size of the cell, stochastic characteristic of the energy source, and the amount of wasted energy (significant amount energy is turned into heat or is reflected by the surface of the cell), it is not a feasible method for some IoT applications such as wearable devices [127]. The simplified structure of a photo-voltaic module is shown in Figure 5a.

5.2.2. Mechanical-Based Energy Harvester

In contrast to solar cells, mechanical harvesters are smaller in size and provide a high power density. For these reasons, they are widely used in IoT applications (from wearable devices to monitoring). The mechanical energy is divided into two groups, kinetic and potential, where the former is generated through motion, vibration, pressure and human activity, and the later one is generated based on the position of the energy source. The mechanical energy harvesters are designed based on three different methods, electromagnetic, electrostatic and piezoelectric. Within these methods, the piezoelectric energy harvesters are light-weight and cost-effective and provide high output voltage, energy density, and capacitance, which make them more suitable for IoT applications [128]. The piezoelectric energy harvesters operate based on the piezoelectric material where the crystal ionizes under a certain strain, and is able to convert kinetic energy to electrical energy. The piezoelectric modules are known as cantilever beam, circular diaphragm, cymbal, and stacked structure [128]. Based on the type of the piezoelectric material and the amount of energy source, these modules provide a wide range of power density from 0.021 μW/mm^3 to 2 W/cm^3 [10,129]. However, these materials are frangible, easy to break, and can be toxic [10]. Figure 5b illustrates the simple structure of the piezoelectric energy harvester.

5.2.3. Dynamic Fluid-Based Energy Harvester

Compared to the solar cells, dynamic fluid energy harvesters have lower power density and have more limitations regarding the installation site. The dynamic fluid energy source is divided into two main types, wind, and water. The most common energy harvester in this category is the turbine. According to the general structure of the turbine, the blades are connected to a shaft that can spin the generator by its rotation. Microturbines (windmill [130] and wind-belt [131]) were designed to make the wind turbine suitable for IoT applications regarding their scale, however, the efficiency of these turbines is decreased by reducing the size of the blades [132]. Moreover, hyper-power turbines that are available in different scales are used for the flowing water energy source. Since this method is flexible in size, pollution-free, and has a continuous source of energy, it is feasible for IoT applications [125]. According to the scale of the harvesters and their installation site, they provide a power density from 1 mW/cm^2 to 41.2 mW/cm^2 [10,133,134]. Nevertheless, turbines have some limitations, such as feasibility only in open, windy, or near the sea areas. Figure 5c shows the basic structure of a dynamic fluid energy harvester.

5.2.4. Thermal-Based Energy Harvester

Compared to the above energy harvesters, thermal energy harvester modules provide a range of power density between solar cells and turbines. Thermal energy harvesters include geothermal, waste heat from the industrial sector, solar heat, or even the human body [125]. The thermocouple or Thermometric Generator (TEG) is a widely known example of thermal energy harvester. It is made of two different metals or semiconductors, which generate a voltage, based on the temperature difference between their two junctions [129]. These harvesters have a long life and low maintenance, however, their low efficiency (5–11%) has prevented them from being widely used in IoT applications [114,125]. According to the type and the reflected heat of the TEG, its power density varies between 40 μW/cm^2 and 50 mW/cm^2 [10]. Figure 5d illustrates a typical model of a TEG made of semiconductors.

5.2.5. Acoustic Noise-Based Energy Harvester

Compared to the above energy harvesters, the lowest power density is generated by the acoustic noise harvester. The energy source of acoustic noise is based on sound waves (longitudinal, transverse, bending, hydro-static, and shears waves) and vibration [125]. According to the functionality of the acoustic noise harvester, they are divided into three main types, Helmholtz resonator-based, quarter-wavelength resonator-based, and acoustic metamaterial based techniques [135]. To generate power from noise waves, first, the noise is directed into the barrier and vibrates in the resonator. Then the converters change the resonance into electricity, which can be stored in the super-capacitors or batteries [135]. Among the aforementioned energy harvesters, acoustic noise harvesters usually provide the lowest power density (up to 960 nW/cm^3), and there are scarce environments with the required level of acoustic noise. Hence, it is only a feasible method for powering up some IoT applications such as infrastructural monitoring [125]. Figure 5e illustrates the basic structure of an acoustic noise energy harvester.

5.2.6. Radio Frequency-Based Energy Harvester

After acoustic noise harvester, Wireless Energy Harvesting (WEH) methods generate the lowest power density among the aforementioned techniques. RF signals are divided into two main groups, dedicated and radiated signals. The former group relies on RF transmitters included in the same IoT system, which usually have predictable features [136], whereas the latter group includes ambient RF signals that are radiated from other sources like TV, GSM, WiFi, microwave, ovens, or radar among others. The fundamental parts of an RF energy harvester are known as the receiving antenna, matching circuit, peak detector, and voltage elevator, which are shown in Figure 5f. The combination of the peak detector and voltage elevator is usually named rectifier and the RF energy harvester is named rectenna. In principle, RF signals are received by an antenna. Then in the matching circuit, the voltage is amplified by matching the antenna impedance to the rectifier circuit. Finally, the rectifier which is a part of Alternating Current/Direct Current (AC/DC) converter, captures the AC signal and converts it to a DC signal [126]. It is possible to store the energy by adding a capacitor (rechargeable battery) to the RF energy harvesting module or power-up, for instance, a passive RFID tag [114]. Due to the simplicity, availability, and easy to implement features of RF signals, WEH methods are a promising solution for IoT systems [137]. However, since the efficiency of RF energy harvesting systems depends on the amount of captured power and AC/DC conversion effectiveness, they are not practical in the rural areas [10]. Based on the physical characteristics and installation site of the WEH, the amount of generated power density by rectenna can vary from 0.1 μW/cm^2 to 300 μW/cm^2 [129,138].

5.3. Compatibility between Communication and Energy Harvesting Technologies

The available amount of energy that is harvested from ambient and non-ambient energy sources by each existing energy harvester is listed in Table 5. Generally speaking, among the aforementioned energy harvesters, solar cells and turbines can provide more power density, however, their large scale and availability are their main drawbacks, and make them mostly suitable for outdoor IoT applications [139]. Moreover, piezoelectric materials that are widely used as mechanical and acoustic noise harvesters suffer from brittleness. Since thermal energy source is independent of environmental conditions and uses a simple harvester system to scavenge the energy, it can be well adopted in different

IoT applications such as healthcare (wearable devices) [140]. However, the main drawback of the thermal energy harvester is its low efficiency. Different IoT applications such as smart city and healthcare can benefit from RF harvesting systems, where the RF signals are converted to electricity to keep those devices powered. Nevertheless, compared to solar cells and turbines, RF harvesters provide lower power density, and RF signal strength depends on the distance between its harvester and the signal source.

Table 5. Various energy harvesting mechanisms.

Energy Source	Energy Harvester	Power Density	Limitation	References
Sun radiation	Photo-voltaic panel	0.15–100 mW/cm^3	Large scale/ Unavailable during night	Zhou et al. [125]
Fluorescent light	Dye Sensitized Solar Cell (DSSC)	10–100 µW/cm^3	Dependent on the indoor light	Zhou et al. [125] Aparicio et al. [126]
Human Body Motion	Piezoelectric	1–2 mW/cm^2 0.2 mW/cm^2	Frangible material	He et al. [10] Grag et al. [129]
Vibration	Electromagnetic Induction	0.2 mW/cm^3 0.3 mW/cm^3	Difficult magnet integration	Grag et al. [129] Zhou et al. [125]
Vibration	Electrostatic conversion	0.021 µW/mm^3	Mechanical stability	Zhou et al. [125]
Wind force	MicroWindbelt	41.2 mW/cm^2	Unavailable in closed area	Laštovička -Medin [133]
Flowing water force	Francis turbine	1 mW/cm^2	Unavailable in closed area	He et al. [10]
Thermoelectric	Thermocouple	40 µW/cm^2 50 mW/cm^2	Low efficiency	He et al. [10] Grag et al. [129]
Acoustic noise	Acoustoelatic Sonic Crystal (AESC)	3 (75 dB) nW/cm^3 960 (100 dB) nW/cm^3	Scarce energy source	He et al. [10] Yuan et al. [135]
Radio Frequency	Wireless Energy Harvester (WEH)	0.1 µW/cm^2 300 µW/cm^2	Unavailable in suburban areas	Adila et al. [138] Grag et al. [129]

The intersection of the available harvested energy from existing energy harvesting technologies (cf. Table 5), and the power consumption IoT technologies analysis from Section 4, defines suitable combinations of these technologies. Due to its low-power consumption, LPWAN technologies like LoRa can benefit from a wide range of energy harvesting technologies like solar panel or thermocouple, making it a promising IoT technology. Another long-range wireless communication technology like IEEE 802.11ah, although having higher power consumption, can benefit from more powerful energy harvesting technologies like solar panel or wind force for outdoor use cases.

Different examples in the literature show that it is possible to provide a certain percentage of the required power for the IoT systems by means of energy harvesting technologies. This amount of harvested energy adds to the battery and prolongs its operational lifetime. For instance, the waste heat from a central heating installation, can extend the operational lifetime of the batteries in a monitoring system powered based on a WiFi communication technology [141]. Based on the size of the solar cells and the amount of illumination of the sun, solar energy harvester modules can keep devices powered by extending the battery's lifetime, which operate under LPWAN technologies [139]. Due to the low power consumption of the WPAN technologies, they can benefit from ambient RF [142] or thermal energy harvesting from the human body [143]. Moreover, a dedicated RF source can keep low-power RFID applications powered [144]. Experimental results combining the existing literature, and the available amount of energy that can be provided by different energy harvesters, are summarized in Table 6. Thus, according to the available power density of these energy harvesting systems (cf. Table 5), they can prolong the battery's lifetime in IoT communication technologies (cf. Table 3), as detailed in Table 6. For instance, a TEG harvester can add about 10% of the IEEE 802.11ah WiFi required power to the batteries of the system, and thus, prolong their lifetime.

Besides the limited harvested power and the hardware related limitations of the energy harvesters, there is a need to improve the IoT communication technologies in terms of energy consumption. In the design procedure of potential wireless communications for IoT, the requirements of energy harvesting systems and their constraints are not well taken into account. Thus, there is a need to change the legacy protocols to accommodate the unpredictable behavior of energy harvesting sources. This requires a comprehensive review of relevant existing energy harvesting MAC protocols in the literature.

Table 6. Experimental analyses in literature on the suitability of specific energy harvesters with IoT technologies [139,141–144].

Energy Harvester	Energy Harvester Feature	IoT Technology	IoT Use Case	Power for IoT Technologies (%)
Solar Panel	38.5–40.7 cm^2	LoRa (13 dBm)	Weather Monitoring	98
TEG	4.5 °C (ΔT)	WiFi (IEEE 802.11ah)	Smart Building	10
Human Body (TEG)	3–15 °C (ΔT)	BLE	Smart Healthcare	3.7
Human Body Motion (Piezoelectric)	Located in the shoe with the speed of 6.44 km/h	Zigbee	Smart Building Smart Healthcare	1.3
Dedicated RF Harvester	Tag size 95 mm × 24 mm	RFID active tag	Industrial Automation	0.3

6. Energy Harvesting MAC Protocols

In Section 3, we provided a comprehensive classification of the recent existing energy-aware MAC mechanisms in the literature for IoT systems. However, since these mechanisms are not designed based on the intermittent nature of the energy harvesting energy sources, they may not provide sufficient energy for these techniques. To fill this gap and enable the integration of the energy harvesting techniques with existing communication technologies, various energy harvesting MAC protocols are proposed in the literature. However, since these protocols have their own benefits and drawbacks, to highlight the characteristics of each energy harvesting MAC protocol, we need to have a precise comparison of the existing energy harvesting MAC protocols.

For this reason, we provide a comparison of existing energy harvesting MAC protocols according to the categorization presented in Section 3. Then, for each channel access category, we consider two sets of parameters, which are not absolute values. The first group of parameters is related to the common features (extracted from the existing literature) of the energy harvesting proposed MAC protocols regardless of their channel access categories, and the second set of parameters is defined based on the specific requirements of each channel access category. Since the parameters from the first set are common among all four categories, we list them at this point, and the specific parameters of each category will be explained within their related category. The common set of parameters include the type of the energy harvester, whether the MAC protocol mechanism is energy-efficient and is designed based on ENO condition, and probabilistic approach. Energy efficiency is an important parameter in the context of energy-aware MAC protocols since their goal is to reduce energy consumption to adapt to energy harvesting. Hence, the listed MAC protocols in Section 3 do not introduce energy efficiency at all, but the MAC protocols in Section 6 try to modify and enhance the Section 3 protocols in a way to increase the efficiency in terms of energy. The ENO condition has not been satisfied in any energy harvesting MAC protocol included in this survey, and it is more like a benchmark for future works. It is worth mentioning that the probabilistic approach in this context means that the MAC protocol makes decisions based on the previously gathered information and refers to the techniques that the MAC mechanisms adopt to manage the available energy of the nodes (estimation of the energy level and dynamic change of the MAC parameters based on the network conditions). Further parameters include whether the MAC mechanisms adapt to the variable amount of available energy or not and prioritize the frame transmission or not. For each energy harvesting MAC protocol, the specific energy management techniques which are deployed in the mechanism, and the type of IoT application that is supported, are highlighted.

In this section, the mechanisms of existing energy harvesting MAC protocols in the literature are explained, then, some of the advantages and disadvantages of these protocols are highlighted. Finally, some of their modifications and enhancements are listed.

6.1. Random Access

In the random access category, the increasing trend of collision rate can be alleviated by balancing the trade-off between collision rate and parameters such as idle listening, overhead reduction, load balancing, and QoS support.

6.1.1. Carrier Sensing-Based Energy Harvesting MAC Protocols

The collision management techniques used to reduce the energy consumption in carrier sensing-based MAC are divided into two main approaches known as channel prioritization and forced to leave the contention.

The first approach is channel prioritization in which the network energy consumption is reduced by adjusting the wake-up duration to the energy level of an individual node and prioritizing the frame transmissions based on their contents. One of the earliest energy harvesting MAC protocols, which is mostly known as the reference mechanism of this approach, is Radio Frequency MAC protocol (RF-MAC) [145]. This protocol intends to balance the trade-off between data frame and energy transmissions at the same frequency band. Also since the data frame transmission is based on the random contention window values, nodes with a high level of energy do not access the channel more than those nodes with a low energy level. Although this protocol reduces some amount of energy consumption of the network, it faces a few challenges, such as long transmission delay due to the random back-off and harvesting procedures and lack of providing the QoS requirements. Since this protocol is designed based on the CSMA method and does not provide time synchronization, optimizing the output power of high-frequency signals with different phases, is another challenge for this protocol.

One solution for the shortcomings of RF-MAC is presented in [146], where an algorithm allows an on demand energy harvesting within contention (back-off) period, to reduce the delay. However, in networks with high traffic and frequent energy harvesting procedure, this MAC protocol still suffers from unpredictable and long transmission delays.

In the second approach, active nodes are randomly forced to leave the contention and go to sleep mode. Consequently some amount of the energy budget of the network is saved. One of the earliest energy harvesting MAC protocols that adopted this approach is Energy-Level MAC protocol (EL-MAC) [147]. This protocol divides the nodes into primary (higher energy) and secondary nodes (lower energy). First, it gives the access channel to the secondary nodes with a lower level of energy and forces the primary nodes to go to sleep mode. For this reason, this protocol conserves energy by reducing the contention level and providing channel prioritization. However, since nodes with a high level of energy are forced to harvest energy while they stay in sleep mode, they lose the opportunity to contend.

Although the second approach improves the trade-off between collision rate and idle listening more than the first approach, neither considers load balancing or overhead reduction as energy-related parameters.

6.1.2. Blind Access-Based Energy Harvesting MAC Protocols

A mathematical model of an energy harvesting MAC protocol, which is designed based on an integration of the RF harvester with the Slotted ALOHA mechanism, is proposed in [148]. According to this mechanism, each node includes a data frame buffer with a single frame capacity and an energy frame buffer with the capacity to transmit a certain amount of energy frames. Data frame transmission for each node requires a specific amount of energy frames. Since in this mechanism, the data frame and energy buffer highly interact with each other, it is able to model only small-sized networks. Also, in this mechanism, long transmission delay reduces the number of arriving energy frames, which increases the data transmission failure.

To reduce the transmission failure in small-size networks, the authors in [149] introduced a Hybrid AP (HAP), which controls frame synchronization and channel access prioritization. An enhancement of harvest-then-transmit protocol [150], defines a dynamic energy harvesting duration for each node to support dense networks, reduce the implementation complexity, and frame transmission overhead. However, delay due to long idle listening duration remains an open issue, and due to the lack of any exact performance measurements, it has not been deployed in wireless environments.

6.1.3. Analytical Discussion of Random Access Category

The aforementioned random access-based energy harvesting MAC protocols are just a few protocols considered as the reference protocols belonging to each approach. Other random access-based energy harvesting MAC protocols are listed in Table 7. As described in this section, most of the protocols focus on collision management techniques, which may increase the idle listening duration, and thus increase the network energy consumption. Moreover [146,151], intend to improve RF-MAC in terms of energy efficiency by applying various energy management techniques such as adaptive contention window algorithm, energy-aware RTS/CTS. However, the ENO concept, which adjusts the performance of the protocol to the chaotic behavior of the harvested energy, is taken into consideration only in [146,152]. In contrast to the carrier sensing approaches [149,150], approaches reduce the overhead. However, in both subcategories, the missing energy-related parameter among the proposed MAC protocols is load balancing. The carrier sensing-based approaches were mainly designed based on in-band RF technique, whereas blind access approaches are considered out-of-band RF technique. A few of the listed MAC protocols in Table 7 are evaluated based on real measurements, while the rest are evaluated through analytical models and simulations. Among all the protocols, QAEE-MAC [153], QPPD-MAC [154] and DeepSleep MAC [155] protocols fulfill most of the energy conservation parameters, which are highlighted in this table.

Table 7. Comparison of random access energy harvesting MAC protocols.

Protocol	EH Technique	Energy Efficient	ENO Consideration	Adaption Respect to Energy	Prioritization Respect to Energy	Probabilistic Approach	Energy Technique Management	Application Support	Collision Management	Idle Listening	Overhead Reduction	Load Balancing	QoS Support
QAEE MAC	Generic Approach	✓	✗	✗	✓	✓	Adaptive CW	Critical/ Urgent Traffic	✓	✓	✗	✗	✓
QPPD MAC	Solar Cell	✓	✗	✓	✓	✓	Wake-up Beacon	Hard to Reach/ Delay Sensitive Application	✗	✓	✗	✗	✓
RF-MAC	In-Band RF	✗	✗	✓	✓	✓	Adaptive CW Beacon	Generic Application	✗	✓	✗	✗	✗
REACH MAC	In-Band RF	✓	✗	✗	✓	✗	Adaptive CW Application	Real Time	✓	✗	✗	✗	✗
HE-MAC	In-Band RF	✗	✓	✗	✓	✓	EDCA/ Adaptive CW	M2M Application	✗	✗	✗	✗	✓
OER-MAC	In-Band RF	✓	✓	✗	✓	✓	On-demand Energy Request	Event-driven Application	✓	✗	✗	✗	✗
EL-MAC	Generic Approach	✓	✗	✓	✓	✓	Adaptive CW	Cognitive Radio Networks	✓	✗	✗	✗	✗
DeepSleep	Ambient Energy Source	✓	✗	✓	✓	✓	Energy Aware DeepSleep/ Controlled Access	M2M Application	✓	✓	✗	✗	✗
W^2P-MAC	In-Band RF	✗	✗	✓	✗	✓	ERTS/ ECTS	N/A	✓	✓	✗	✗	✗
CEH-MAC	Generic Approach	✓	✗	✓	✓	✓	Cooperation of Harvested Energy and Data	Healthcare Application	✗	✓	✗	✗	✗
Sakakibara et al.	Out-of-Band RF	✓	✗	✗	✗	✓	Queuing Mechanism	N/A	✓	✗	✗	✗	✓
Hadzi-Velkov et al.	Out-of-Band RF	✗	✗	✗	✗	✓	Energy Queue/ HAP	Generic Application	✓	✗	✗	✗	✓
Choi et. al	Out-of-Band RF	✗	✗	✗	✓	✓	HAP	N/A	✗	✗	✓	✗	✗
Harvest-Until Access	In-Band RF	✗	✗	✗	✗	✓	HAP	N/A	✓	✗	✓	✗	✗

6.2. Scheduled Access

In the scheduled access category, node synchronization is one of the main issues that have an impact on the energy consumption of the network [156]. Other energy-related parameters that need to be taken into account for this category include end-to-end delay, resource allocation, overhead, and interference.

6.2.1. Channelization-Based Energy Harvesting MAC Protocols

Predefined frame assignment avoids collision and makes the idle listening duration unnecessary. However, fixed assignment methods require global time synchronization, which increases the overhead and thus increases the network energy consumption. Among all methods of this category, TDMA tackles overhead issues more efficiently.

One of the reference protocols in this subcategory is the Energy Harvesting TDMA (EH-TDMA) [156], which assigns predefined frames to the nodes for data transmissions, and controls these transmissions by sending a small frame known as a ping message. In the EH-TDMA MAC, all nodes have the responsibility to harvest the energy whenever possible. EH-TDMA is designed for single-hop scenarios, and improves channel utilization, interference reduction, and is evaluated based on the simulations on the three different radio platforms. Since the EH-TDMA mechanism does not provide an energy management method to estimate the future energy level based on the existing level of energy, it cannot manage the energy budget of dense networks and intermediate nodes efficiently and may not be practical for them.

The network energy consumption can be managed through NOMA-based approaches. In [157], the protocol dynamically defines the duration of energy transfer based on the number of active nodes in the network, to optimize resource allocation. Since this modification does not consider the future energy level of each node, it faces a long delay due to global time synchronization. Another NOMA-based modification of EH-TDMA MAC protocol is proposed in [158], where the transmission power is reduced to support dense networks. Although these protocols manage network energy consumption, they suffer from hardware (especially receiver) and computational complexity.

6.2.2. Controlled Access-Based Energy Harvesting MAC Protocols

The proposed MAC protocols in this subcategory are primarily designed based on the polling method rather than the token passing method.

One of the earliest energy harvesting MAC protocols in this subcategory is a Probabilistic Polling mechanism (PP-MAC) [159], which is evaluated based on real measurements. This protocol broadcasts a defined contention probability through the network. The coordinator adjusts this value based on the network conditions, such as the energy harvesting rate of each node and the size of the network, which can be changed dynamically. Although PP-MAC protocol provides fairness in the network, it changes to network dynamics very slowly, which increases the transmission delay and cannot support scenarios with intermediates nodes, interference, and hidden terminal issue.

One solution to address these shortcomings is the method Estimated Number of Active Neighbors (ENAN) [160], which dynamically adjusts the contention probability to the energy harvesting rate, thus reducing the collision rate and the number of polling frames simultaneously. In contrast to polling-based mechanisms, which face long delays due to synchronization, token-based mechanisms reduce it by eliminating the synchronization from the channel management procedure.

Although the channelization-based protocols require global synchronization, control access-based mechanisms such as Probabilistic Polling and Token passing require local synchronization, and thus they can reduce the transmission delay. However, two crucial energy-related parameters, overhead and high channel utilization, are missed in the scheduled access-based energy harvesting MAC protocols.

6.2.3. Analytical Discussion on Scheduled Access

The aforementioned scheduled access-based energy harvesting MAC protocols are just a few protocols that can be considered as the reference protocols belong to each approach. Other scheduled access-based energy harvesting MAC protocols are listed in Table 8. As described in the table, most of the proposed energy harvesting MAC protocols belong to this category, are equipped with RF energy harvesters to prolong the lifetime of the wireless devices. However, these protocols do not consider the ENO concept and cannot reduce the energy consumption of the communication process. Also, they apply various energy management techniques such as power allocation and grouping strategy to reduce the energy consumption of the network. Some of the presented MAC protocols in Table 8 are evaluated based on the empirical measurements whereas, others perform simulations. Among all these protocols, EH-TDMA MAC [156] and EH-MAC [160] satisfy more features towards the MAC layer energy conservation.

Table 8. Comparison of scheduled access energy harvesting MAC protocols.

Protocol	EH Technique	Energy Efficient	ENO Consideration	Adaption Respect to Energy	Prioritization Respect to Energy	Probabilistic Approach	Energy Technique Management	Application Support	Delay Reduction	Synchronization Required	Overhead Reduction	High Channel Utilization	Interference Consideration
EH-TDMA MAC	Ambient Energy Sources	✓	✓	✓	✗	✓	Adaptive Wake-up Time to Energy Level	N/A	✗	✓	✗	✓	✓
TR-EH-TDMA MAC	In-Band RF	✗	✗	✗	✗	✓	N/A	Heterogeneous Networks	✗	✗	✗	✗	✓
D-TDMA MAC	In-Band RF	✗	✗	✗	✗	✓	N/A	N/A	✗	✗	✗	✗	✓
NOMA-MAC	In-Band RF	✗	✗	✗	✗	✓	N/A	N/A	✗	✓	✗	✗	✓
NOMA-HeTNeT MAC	In-Band RF	✓	✗	✗	✓	✓	Sub-channel Allocation/ Power Allocation Algorithms	Heterogeneous Networks	✗	✗	✗	✗	✓
NOMA+TDMA MAC	In-Band RF	✓	✗	✗	✗	✓	Grouping Strategy/ SCA Algorithm	N/A	✗	✓	✗	✗	✓
PP-MAC	Solar Cell/ Thermal	✓	✗	✓	✗	✓	Contention Probability Adjustment	Monitoring Application	✓	✓	✓	N/A	✗
MTPP-MAC	Solar Cell	✓	✗	✓	✗	✓	Grouping Strategy	Generic Application	✓	✗	✗	N/A	✓
EH-MAC	Ambient Energy Sources	✗	✗	✓	✗	✓	Contention Probability Adjustment AIMD/ENAN	Event-Driven Application	✓	✓	✓	N/A	✓
V.B. Mišić et al.	In-Band RF	✓	✗	✓	✗	✓	Wake-up/Sleep	Generic Application	✓	✗	✗	✗	✗
M.S.I.Khan et al.	In-Band RF	✓	✗	✓	✗	✓	Queuing Mechanism	Generic Application	✓	✗	✗	✗	✓
EDF-HEAP MAC	Ambient Energy Sources	✗	✗	✓	✓	✓	Earliest Deadline First Polling	Monitoring Application	✗	✗	✓	✗	✗
Fair-Polling MAC	Ambient Energy Sources	✗	✗	✓	✓	✓	Contention Probability Adjustment	Monitoring Application	✗	✗	✗	✓	✗
Token-MAC	In-Band RF	✗	✗	✓	✗	✓	N/A	Inventory Management/ Asset Tracking	✓	✗	✗	✗	✗

6.3. Hybrid Access

In hybrid access category, due to the combination of random and scheduled access categories, the main issues that impact the energy consumption of the network are collision rate and node synchronization. The relevant parameters to collision management are overhead, load balancing, QoS requirements, and grouping strategies. At the same time, the relevant parameter to node synchronization is resource allocation. In this subsection, we list such hybrid schemes that combine random and scheduled access.

6.3.1. Combination of Blind Access and Channelization Subcategories

One of the earliest versions of the Dynamic Frame ALOHA (DFA) MAC protocol with energy harvesting is introduced in [161]. In this protocol, a coordinator node initializes a query command, which synchronizes the nodes and schedules the order of channel access for each node. Then each node, which is equipped with an energy storage device and a harvester, is allowed to start the data transmission procedure at an inventory round according to the DFA mechanism. The authors highlighted that the frame size needs to be dynamically adjusted to the energy harvesting rate and energy level of the nodes. Moreover, the required energy of each frame depends on the reception of a query message, acknowledgment, or transmission of a data frame. This protocol is evaluated based on a mathematical model and intends to provide a balance between the complexity level of implementation and the size of the network. However, this protocol suffers from high level of energy consumption, due to the node synchronization and the increasing trend of collision rate under high traffic load.

To alleviate energy wastage due to node synchronization, an ALOHA-based approach is presented in [162] which defines a grouping procedure. In this protocol, instead of individual node synchronization, the synchronization is defined for each group of nodes, and thus the energy wastage due to this issue is decreased. Another enhancement of the DFA MAC protocol is presented in [163]. Collision rate reduction is achieved by combining the NOMA method with the SA method, where the nodes start transmission based on different predetermined power transmissions. Nevertheless, addressing some energy-related parameters such as long transmission delay, overhead reduction, load balancing and QoS requirements still remain unsolved.

6.3.2. Combination of the Carrier Sensing and Channelization Subcategories

An early energy harvesting MAC protocol based on the combination of CSMA/CA mechanism and TDMA method is an adaptive energy harvesting MAC protocol, which is proposed in [164]. This protocol divides the frame into four different parts. In the first period, the controller node sends a notification to all the nodes to prepare them for the energy harvesting period. In the second period, only nodes that contain a frame can start harvesting energy. Then in the third period, these nodes start to contend to access the channel based on the CSMA/CA mechanism. In this phase, according to the energy level of each node, a certain contending probability is assigned to them (nodes with a lower level of energy have a higher contending probability). In the end, the successful nodes transmit data frames according to the TDMA method. This protocol is evaluated based on a mathematical model, which reduces the transmission delay, number of collisions and optimizes the energy harvesting period. Hence, in this protocol, energy harvesting is fulfilled in an out-of-band manner, no interference occurs between energy and data frame transmissions. However, in the case of in-band energy transfer, the MAC protocol needs to be designed in a way to avoid energy and data frame interference.

One solution to this issue is presented in [165], where an interference cancellation technique is applied to make sure that all the nodes have sufficient energy to operate, and utilizes an adaptive sleep duration management to provide node synchronization and reduce the collision rate. Another method to prevent the energy and data frame interference is the clustering approach, which is presented in [166]. For this reason, the active time of the cluster heads is reduced to an optimal value. However, providing individual charging time for each node, or using a clustering approach, make these protocol implementation complex for the coordinator and they cannot meet the QoS requirements.

6.3.3. Combination of Carrier Sensing and Controlled Access Subcategories

An example of this technique is Human Energy Harvesting for WBANs (HEH-BMAC) [47] protocol, which is evaluated based on extensive simulations and can be applied to realistic networks. The main target of this protocol is to prioritize channel access based on the data traffic type. Hence, the data traffic load is divided into two types, data with high priority and data with normal priority. The ID-Polling MAC protocol, which provides contention-free channel access, is used for high priority transmissions, and CSMA is used for nodes with regular priority transmissions. The HEH-BMAC dynamically schedules the duration of each procedure based on the energy level of nodes. According to the authors, this protocol adapts to the changes in network size and energy harvesting rate and reduces the transmission delay. However, mathematical evaluation of the proposed MAC protocol, QoS of the network, and introducing a smart energy-efficient algorithm have been considered as the future work.

An early enhancement of this protocol [167] intends to reduce the collisions and move towards a smart energy-efficient approach. For this reason, it combines a wake-up/sleep scheduling approach and ENAN mechanism (where the coordinator node frequently updates the polling probability), to reduce the number of missed poll frames, and thus decreases the number of re-transmissions. However, transmission delay has not been evaluated in this work and is considered as an open issue. Similar to HEH-BMAC, this protocol has not been designed for ENO conditions, and supporting QoS and load balancing as energy-related parameters remain open challenges.

6.3.4. Switching from Random Access to Scheduled Access Categories

The Receiver-Initiated Harvesting-aware MAC (RIH-MAC) protocol [168] adopts a fixed assignment reservation method in direct communications, where a controller schedules the frame transmission procedure according to the information of nodes. In contrast, in the absence of the controller node (ad hoc), it operates based on the CSMA/CA mechanism. In both cases, the transmission procedure is started when the receiver has harvested enough energy to send the Ready to Receive (RTR) message to the nodes. Then, these nodes are only allowed to send their data frames after the reception of the RTR message. The RIH protocol adapts to the size of the network and reduces the number of collisions. Hence, it saves some amount of energy budget of the network. However, it still suffers from the hidden terminal issue and long transmission delay.

6.3.5. Duty-Cycled-Based Energy Harvesting MAC Protocols

The reference MAC protocols based on this approach are two dynamic wake-up/sleep scheduling protocols known as Duty-cycle Scheduling based on Residual energy (DSR) and Duty-cycle Scheduling based on Prospective increase in residual energy (DSP) [169]. The DSR protocol reduces the delay duration due to the sleep mode, while the DSP protocol adjusts the duration of wake-up/sleep mode to the estimation of the increasing amount of the residual energy based on the available harvested energy (it reduces the sleep latency). These two protocols are evaluated based on extensive simulations utilizing Network Simulator 2 (ns-2).

One of the modifications of these two protocols, which intends to reduce the energy wastage during the idle listening mode, is proposed in [170]. ODMAC protocol adjusts the wake-up/sleep duration to the current residual energy of each node and saves the energy budget of the network. However, it faces two unsolved issues, it does not apply any mechanism to control frame re-transmissions and it suffers from the hidden node problem. To address the energy wastage due to the re-transmission an exponential decision MAC is introduced in [171], where the wake-up/sleep scheduling is defined based on the future residual energy of each node (intelligent scheduling). Although this protocol outperforms ODMAC in terms of energy consumption, it does not point to the hidden node issue and its computational complexity costs a longer transmission delay. A more recent enhancement of DSR and DSP protocols is proposed in [172], where not only wake-up/sleep scheduling, but also the contention window, is adjusted to the amount of harvested energy and energy harvesting rate. This protocol outperforms ODMAC and ERI-MAC in terms of network energy consumption by reducing the level of contention. However, the performance of this protocol has not been evaluated under dense networks condition.

A realistic evaluation is performed in [173] based on the Synchronized Wake-up interval MAC (SyWiM) protocol. This protocol benefits from a solar cell and is designed based on the Receiver Initiated Cycled Receiver (RICER) MAC protocol. It intends to improve the QoS, reduce the delay, load balancing, and total energy consumption of the network by considering the ENO condition. According to this protocol, nodes stay in a harvesting or a non-harvesting period. The energy consumption of the non-harvesting period is reduced by dynamic adaptation of the wake-up/sleep interval to the residual energy of the node, and in the harvesting period, this interval adapts to the harvested energy. The SyWiM protocol is validated on a real implementation; however, by increasing the number of nodes, the performance of the network may be affected. In duty-cycled-based energy harvesting MAC protocols, balancing the trade-off between energy conservation and transmission delay still is a challenge. Moreover, introducing new methods of wake-up/sleep adjustment to the features of the battery, such as available energy in a battery, its capacity of loss, and charging profile, remain open issues.

There is two main differences between duty-cycled-based energy harvesting MAC protocols and other hybrid-based ones. First of all, thanks to the duty-cycle techniques, these protocols balance the trade-off between collision rate and idle listening duration. The second difference relates to their capability to support QoS.

6.3.6. Analytical Discussion on Hybrid Access Category

The aforementioned hybrid access-based energy harvesting MAC protocols are just a few that can be considered as the fundamental protocols in this category. Other proposed protocols, which are listed in Table 9, mainly reduce the energy consumption of the network by applying energy management techniques such as adaptive wake-up/sleep scheduling, probabilistic contention, and collision management. However, they still do not consider the ENO concept. Due to the combination of the random and the scheduled access, the deployed energy harvesting techniques in the hybrid access protocols can be adapted to a random access approach or a scheduled one. Also, these protocols support a wide variety of application types from healthcare applications (HEH-BMAC [47]) to M2M applications (DFSA and EH-RDFSA [174,175]). Among all these protocols, the AH-MAC [166] and SyWiM [173] are two protocols, which support most of the listed parameters and have been evaluated through a real test-bed.

6.4. Cross-Layer

The energy-related parameters in this category are taken from the lower layer (power transmission) or upper layer (optimal path selection) of the MAC layer in the IoT protocol stack, whose information helps the MAC layer to make an optimal decision. Also, other parameters, such as grouping strategy and the number of connected layers, can express useful information regarding the complexity of the implementation of the proposed approach. In the following subsection, existing literature on other protocol layers that assist the MAC in improving the energy efficiency are explained.

6.4.1. Interaction between the Physical Layer and MAC Layer

The presented MAC protocol in [176] intends to combine information of the physical layer with the MAC layer performance. It dynamically adjusts the duration of the wake-up/sleep scheduling and the transmission power to the harvested energy level and the quality of the link. These adjustments are jointly made based on the Exponentially Weighted Moving-Average (EWMA) algorithm and the last Received Signal Strength Indicator (RSSI). This cross-layer mechanism deploys a Transmitter Initiated Cycled Receiver MAC (TICER) protocol to manage the contention level of the channel. The proposed protocol is implemented in the PowWow [177] platform, with a solar cell and a super capacitor to save the harvested energy. This protocol is evaluated based on a realistic network and provides energy efficiency in a real IoT system.

6.4.2. Interaction between the MAC Layer and Network Layer

The Opportunistic Wake-Up MAC (OPWUM) [178] protocol which belongs to this subcategory, benefits from the information of the routing table and hence, reduces the energy consumption of the transmissions. This protocol operates based on the CSMA/CA mechanism and selects the receiver node among several receivers in an opportunistic manner (opportunistic forwarding). The transmission procedure is started when a node sends the RTS frame to all the potential receivers. Then, the potential receivers adjust their back-off timers to the state of a specific metric, which is defined according to the application requirements. For instance, one metric can be the level of residual energy. In this case, the receiver nodes with a higher level of residual energy have a higher priority to respond to the node. The OPWUM protocol is evaluated based on a mathematical model and then is implemented in GreenCastalia. This protocol reduces the level of contention and total energy consumption of the network. However, other parameters, such as transmission delay and network size, are not considered.

6.4.3. Interaction between the Physical, MAC, and Network Layers

The cross-layer approach, which is presented in [67], aims to balance the trade-off between energy consumption and the duration of the wake-up/sleep scheduling approach. This protocol deploys a geographic routing protocol known as Two-Phase Geographic Greedy Forwarding (TPGFPlus) at the network layer, and it adjusts the transmission power to the residual energy level at the physical layer. The MAC layer of this method operates based on the Connected K-Neighbourhood (CKN) sleep scheduling algorithm. This algorithm periodically adjusts the wake-up/sleep duration to the residual energy level of the nodes. Each node decides to stay in sleep mode or active mode based on the collected information from the two-hop neighbor locations, energy harvesting rate, residual energy, and the energy consumption of the network. This dynamic decision reduces the number of collision rate; however, different energy-related parameters such as load balancing, overhead reduction are not addressed in this protocol.

The Cross-Layer MAC Energy Harvesting Sensor Node (CL_EHSN) [179] is another protocol that belongs to this group. In the CL_EHSN protocol, first of all, a path is established between two nodes with the help of routing protocols. Then, the MAC protocol based on this information decides about the next-hop nodes. The fundamental of the MAC protocol is based on the four-way handshaking CSMA/CA mechanism and is responsible for determining the charging and active duration of the node. According to the residual energy level of each node, the node decides whether to start the transmission procedure or to start harvesting energy. For this purpose, the node sets its antenna at Transmit/Receive (Tx/Rx) mode and then switches its antenna to energy harvesting mode for the rest of the time. The CL_EHSN provides a flexible and energy-efficient discovery path method. Also, in the case of the dense network, the CL_EHSN outperforms conventional protocols in terms of long transmission delay issues.

6.4.4. Analytical Discussion on Cross-Layer Category

Table 10 summarises the characteristics of energy harvesting MAC protocols based on the cross-layer approach. The main target of these protocols is to satisfy the ENO concept and then evaluates them based on a real implementation. These protocols mostly benefit from the adaptive wake-up/sleep scheduling technique. Among all the mentioned protocols in Table 10, the CL_EHSN MAC addresses most of the parameters that need to be considered towards enabling energy harvesting techniques in wireless communication systems. Since hybrid access and cross-layer approaches are designed based on the combination and integration of different techniques and layers of the network model, these approaches may increase the computational process of the protocol which requires further optimizations. Although the Low Energy Self-Organizing Protocol (LESOP-MAC) [54] does not consider an energy harvesting technique, it makes the integration of the energy harvesting techniques possible.

Table 9. Comparison of hybrid access energy harvesting MAC protocols.

Protocol	EH Technique	Energy Efficient	ENO Consideration	Adaption Respect to Energy	Prioritization Respect to Energy	Probabilistic Approach	Energy Technique Management	Application Support	Collision Management	Overhead Reduction	Load Balancing	QoS Support	Efficient Resource Allocation	Node Grouping	Packet Fragmentation	Synchronization Required
DFA	Ambient Energy Sources	✗	✗	✓	✗	✓	Backlog Estimation Algorithm	Energy Constrained IoT Systems	✓	✗	✗	✗	✓	✗	✗	✓
FA	Generic Approach	✗	✗	✓	✗	✓	Backlog Estimation Algorithm	Generic Application	✗	✗	✗	✗	✓	✗	✗	✓
EG-DFA	Ambient Energy Sources	✓	✗	✓	✗	✓	Backlog Estimation Algorithm	Critical/ Urgent Application	✓	✗	✗	✗	✗	✓	✗	✗
HE-MAC	Generic Approach	✗	✗	✓	✗	✓	N/A	Generic Application	✓	✗	✗	✗	✓	✗	✗	✗
FSA	Solar Panel	✓	✓	✓	✗	✓	EWMA/ Wake-up/Sleep	Automatic Meter Reading Application	✗	✗	✗	✗	✗	✗	✗	✓
DFSA	Ambient Energy Sources	✓	✗	✓	✓	✓	Markov Chain Model	M2M Application	✓	✗	✗	✗	✗	✗	✗	✓
EH-RDFSA	Generic Approaches	✓	✗	✓	✗	✓	Markov Chain Model	M2M Application	✓	✗	✗	✗	✓	✗	✓	✗
AT-MAC	Generic Approach	✗	✓	✓	✗	✓	N/A	Healthcare Monitoring	✓	N/A	N/A	N/A	✓	✗	✗	✓
PLoRa	Solar Cell and RF Signals	✓	✗	✗	✗	✓	ON-OFF Keying Technique	Various IoT Application	✓	✗	N/A	N/A	✗	N/A	✗	✓
SAN	In-Band RF	✓	✗	✗	✗	✓	SIC/JD	NGIoT Application	✓	✗	✗	✗	✓	✓	✗	✓
Y.Liu et al.	Ambient Energy Sources	✓	✗	✓	✓	✓	N/A	M2M Application	✓	✗	✗	✗	✗	✗	✗	✗
FarMAC	In-Bnad RF	✓	✗	✓	✓	✓	Wake-up/Sleep	Data Collection Application	✓	✗	✗	✗	✗	✓	✗	✓
AH-MAC	Solar Panel	✓	✗	✓	✗	✓	Wake-up/Sleep Modified Synchronization	Low-Rate Monitoring Application/Event-Driven Alarm	✓	✓	✓	✗	✓	✓	✗	✓
HEH-BMAC	Human Body Energy Sources	✓	✗	✓	✓	✓	Probabilistic Contention	Healthcare Application	✓	✗	✗	N/A	✓	✗	✗	✗
RIH-MAC	Piezoelectric	✗	✗	✓	✗	✓	RTR Packet/ Coordinated Energy Consumption Schedule	Nano-Scale Monitoring	✓	✗	✗	✗	✗	✗	✗	✓
H-MAC	Solar Cell	✓	✗	✓	✓	✓	Wake-up/Sleep	Heterogeneous Networks	✓	✗	✗	✗	✓	✗	✗	✗

Table 9. *Cont.*

Protocol	EH Technique	Energy Efficient	ENO Consideration	Adaption Respect to Energy	Prioritization Respect to Energy	Probabilistic Approach	Energy Technique Management	Application Support	Collision Management	Overhead Reduction	Load Balancing	QoS Support	Efficient Resource Allocation	Node Grouping	Packet Fragmentation	Synchronization Required
DSR-MAC DSP-MAC	Solar Panel	✗	✗	✓	✗	✓	Wake-up/ Sleep Scheduling	Generic Application	✓	N/A	N/A	✓	✗	✗	N/A	✗
OD-MAC	Ambient Energy Sources	✗	✓	✓	✗	✓	Opportunistic Forwarding	Low-Delay/ Delay Sensitive Application	✓	✗	✓	✗	✗	✓	N/A	✓
A-MAC	Ambient Energy Sources	✗	✓	✓	✗	✓	Opportunistic Forwarding	Delay-Sensitive Application	✓	✗	✓	✗	✗	✗	N/A	✗
ERI-MAC	Ambient Energy Sources	✓	✓	✓	✓	✗	Queuing Mechanism	Realistic Traffic Model	✓	✓	✗	✓	✓	✗	N/A	✓
RF-AASP	In-Band RF	✓	✗	✓	✓	✓	Adaptive CW/Adaptive Beacon Order Superframe Order	Application with Variable Traffic Conditions	✓	✗	✗	✓	✓	✗	N/A	✓
EA-MAC	In-Band RF	✓	✗	✓	✗	✓	Adaptive Contention Algorithm	Environmental Monitoring	✓	✗	✗	✗	✗	✓	✗	✗
SEHEE MAC	Solar Cell	✓	✗	✓	✗	✓	Slotted Preamble Technique for Wake-up/ Sleep Scheduling	Habitat Monitoring	✓	✗	✗	✗	✗	✗	N/A	✗
PS-EHWSN MAC	Generic Approach	✓	✗	✓	✓	✓	Determining Next Period Sleep Period/ LPL	N/A	✓	✗	✗	✗	N/A	✗	N/A	✗
EEM-EHWSN MAC	Generic Approach	✓	✓	✓	✗	✓	Wake-up/ Sleep Scheduling	Application with Periodic Traffic	✓	✗	✓	✗	N/A	✗	✗	✗
WURTICER MAC	Generic Approach	✓	✓	✓	✗	✗	Wake-up/Sleep Scheduling	Monitoring Application	✗	✗	✗	✓	N/A	✗	N/A	✗
LEB-MAC	Solar Cell	✓	✗	✓	✓	✓	Fuzzy Logic	N/A	✓	✗	✓	✓	✓	✓	✓	✗
ED-MAC	Generic Approach	✓	✗	✓	✗	✓	ED-CR/ ED-PIR	N/A	✓	✗	✗	✗	✗	✗	N/A	✗
SyWiM	Solar Cell	✓	✓	✓	✗	✓	Wake-up Variation Reduction Power Management	Monitoring Application	N/A	✓	✓	✓	✓	✓	N/A	✓

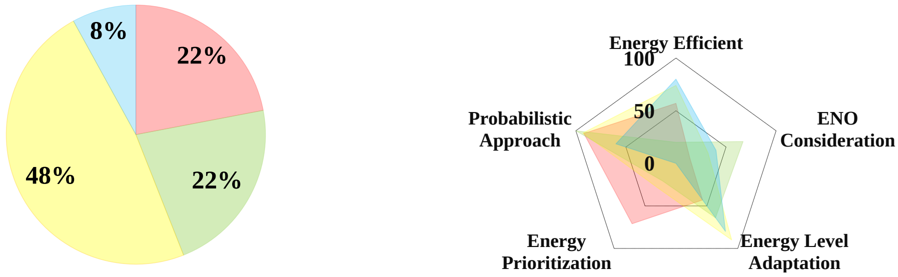
Table 10. Comparison of cross-layer energy harvesting MAC protocols.

Protocol	EH Technique	Energy Efficient	ENO Consideration	Adaption Respect to Energy	Prioritization Respect to Energy	Probabilistic Approach	Energy Technique Management	Application Support	Optimal Path Selection	Adjusted Transmission Power	Number of Connected Layers	Node Grouping
Castagnetti et al.	Solar Cell	✓	✓	✓	✗	✗	Wake-up/Sleep	Monitoring Application	N/A	✓	2	✗
OPWUM	Solar Panel	✓	✗	✓	✗	✓	Wake-up/Sleep/ Timer-based Contention	Monitoring Application	✓	✗	2	✗
TPGFPlus	Solar Cell	✗	✗	✗	✗	✗	Wake-up/Sleep	Generic Application	✓	✓	3	✓
CL_EHSN	In-Band RF	✓	✓	✓	✗	✓	Wake-up/Sleep /Harvesting Time	Generic Application	✓	✓	3	✓
LESOP-MAC	N/A	✓	N/A	✓	✗	✓	Wake-up/Sleep	Surveillance Application	N/A	✗	2	✗

7. Open Issues and Research Challenges for Energy Harvesting MAC Protocols within IoT Systems

According to Table 5, energy harvesters provide a wide range of output power from 3 nW to 100 mW, which is produced by an AESC and a solar cell, respectively. Moreover, energy models, which are explained in Section 4 show that the power consumption of wireless communication technologies is much higher than the scavenged energy through the well-known energy harvesters listed in Table 5. For instance, according to Table 6, a radio frequency antenna which provides a power density of at most 0.3 mW/cm^2, cannot support IEEE 802.11ah frame transmission in different applications such as agricultural monitoring (mean current consumption 0.12 mA) or smart metering (mean current consumption 0.045 mA). Since IoT systems include a large number of devices with limited size, the energy insufficiency which lies between the energy harvester device and wireless communication device power consumption becomes worse.

In IEEE 802.11, around 80% of the total energy budget of the whole network is wasted by the MAC layer anomalies (collision frame, idle listening, overhearing, overhead) [180]. Thus, as mentioned in Section 6, to make the energy harvesters applicable for integrating with the existing wireless communication technologies and alleviate the energy wastage of MAC layer anomalies, different enhancements or modifications of the currentenergy-efficient MAC approaches in the literature are proposed. A comparison of the common feature of the energy harvesting MAC mechanisms, which are explained in Section 6 is summarized in Figure 7. From this figure, it can be perceived that among the selected energy harvesting MAC protocols, cross-layer mechanisms propose the most energy-efficient methods by considering energy level adaptation. In the random access category, 57% of the protocols are energy-efficient, whereas in the hybrid access category, this value increases to 74%, and 90% of these hybrid protocols adapt to the energy level of the node. In contrast to the random and the scheduled access categories that allocated 14% and 67% of the protocols to ENO condition, in the hybrid access category 32% of the protocols consider this condition. Also, according to the analysis results (cf. Figure 7), 23% of the existing energy harvesting MAC protocols in the literature consider the ENO condition, which is the key parameter in IoT systems equipped with energy harvesters. To address energy efficiency in energy harvesting MAC protocol designs, 66% of related works have applied different energy optimization methods and energy management techniques. Although 90% of the MAC protocol designs have adopted a probabilistic approach, 73% of them schedule the node transmissions based on the available level of the energy in the node, and only 34% prioritize the transmission of the nodes with a lower level of energy. Figures 6 and 7 convey that, since only a reduced set of features have been considered in the design of the proposed energy harvesting MAC protocols, there still exists room for improvement in designing energy harvesting MAC protocols. Also, they show that reflecting all the essential considerations to enable energy harvesting techniques at the MAC layer remains a challenging issue, specifically in hybrid access and cross-layer categories that can optimize the performance of MAC layer operations.



(**a**) Category-based distribution of energy harvesting MAC protocols

(**b**) Energy-related parameter comparison

MAC Protocol Category		Energy Efficient(%)	ENO Consideration(%)	Energy Level Adaptation(%)	Energy Prioritization(%)	Probabilistic Approach(%)
Random Access		57	14	43	71	92
Scheduled Access		50	67	64	21	100
Hybrid Access		74	32	90	29	93
Cross-Layer		80	40	80	0	60

Figure 6. Category-based comparison of energy-related parameters in energy harvesting MAC protocols.

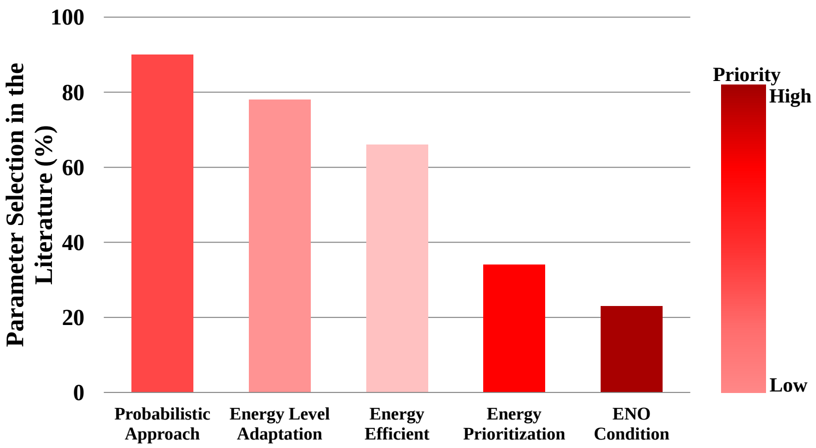


Figure 7. General comparison of energy-related parameters in energy harvesting MAC protocols.

In the first part of this section, we will list the energy wastage at each level of IoT systems, and then we will focus on the role of MAC layer operations regarding energy wastage. In the second part of this section, we will expand the existing challenges that can lead to future research in these topics.

7.1. Essential Considerations to Make MAC Protocols Applicable for Energy Harvesting Techniques

To enable energy harvesting techniques at the MAC layer within the communication level of IoT systems, different challenging issues need to be considered. The most relevant considerations are described next.

7.1.1. Energy Optimization at Different Levels of IoT Systems Architecture

IoT systems are defined by academia and industry based on three levels known as, management level, communication level, and end device level. Our focus in this paper is the optimization at the communication level. The most relevant approaches in the literature to achieve this goal are described next.

1. Optimization at management level
   The management level in IoT systems architecture refers to data centers and cloud computing. Estimations show that around 1% of the worldwide energy budget is spent in data centers [181], thus different works in the literature [182–184] have been oriented towards optimizing the energy consumption at the management level. Along with these methods, in LoRa and Sigfox proprietary standards duty-cycle regulations, which are defined at the management level, can manage the energy consumption of the network by setting the duty-cycle at 0.1% and 1.0% duty cycle per day based on the channel (in Europe). However, since the MAC layer operations do not have a direct connection with this level, the energy optimization at the management level is out of the scope of our study.
2. Optimization at communication level
   At the communication level of the IoT system architecture, the energy consumption of the networks (including those equipped with energy harvesters) can be optimized through different approaches. One approach is the cross-layer framework design [185], which may exclude network and transport layers from the IoT protocol stack to avoid operations of these two layers, or use the information from the network and physical layers to enhance the performance of the MAC layer operations. However, merging different layers of IoT protocol stack is a challenging issue and requires some predefined standardization [185].
   The second approach refers to the optimized energy consumption of the network by selecting the best placement of the gateways or APs [186]. In this approach, each gateway can create a cluster to address specific constraints such as connectivity coverage range, shortest path selection, transmission power, and resource allocation. This grouping strategy could help the MAC layer to optimize the transmission scheduling according to the requirements of each group. Although grouping strategy can be a challenging issue in terms of prediction models, it may reduce the number of required sensors to fulfill a measurement.
   The third approach refers to various PSMs that are deployed in different wireless communication technologies. These methods mainly send the node to the sleep mode state to save energy, however changing the sleep mode to wake-up mode several times has some drawbacks such as long delay. For this reason, there has been many studies in the literature to balance the trade-off between PSMs and other KPIs of the network [155], however, this issue still requires more attention.
   The fourth approach refers to the application layer IoT protocols like Constrained Application Protocol (CoAP) and Message Queue Telemetry Transport (MQTT). Since these protocols are considered lightweight protocols with small header sizes, they reduce the energy consumption of the network. However, due to their lack of direct impact on the MAC layer, a study on them is out of the scope of this study.
3. Optimization at sensing and perception level
   This level mainly includes sensors, actuators and edge devices, which interact with the environment. For this reason, the optimization methods are designed for processor, and wireless transmitters. For instance, one approach is WUR, which is designed based on the communication range and other characteristics of the networks, however it suffers from wake-up beacon collisions. For this reason, designing an energy-efficient WUR is a challenging issue, which has been addressed in literature [24] and but still requires more research.
   The other approach refers to optimizing the central unit processing-memory related power consumption in IoT end devices. This approach is more challenging for non-real time applications, which require a prediction of the deadline, arrival time, and workload of each task beforehand. For instance [187] proposes a dynamic voltage and frequency scaling method, which can adapt to the nature of the non-real time

applications by using a machine learning algorithm. The authors demonstrated that their proposed algorithm reduces 42% of the Central Processing Unit-memory (CPU-memory) related energy consumption.

Besides, in the CL_EHSN cross-layer mechanism [179], which is explained in Section 6, the processor-memory related power consumption can be reduced through the energy-aware MAC, which makes the decisions based on the status of the battery, and estimating the charging time.

The implementation complexity of the MAC protocol, or its algorithms, is another issue that consumes some parts of the network energy consumption. Since complex algorithms require more computation time, they may consume more energy. Nevertheless, the optimization methods complexity should be suitable to the requirements of each level. For instance, channel access complexity should be managed by the central units or APs and should not move to the sensing level.

7.1.2. Energy Optimization for Different MAC Anomalies

According to Section 6, IoT systems benefit from different channel access mechanisms. However, each mechanism has its own drawbacks. For instance, in random-based access mechanisms, energy is wasted due to the re-transmissions, and extra overhead exchanging frames. In scheduled-based access mechanisms, the energy wastage is caused due to the node synchronization or idle slots. The most relevant reasons why MAC protocols in wireless communication devices waste energy are detailed next.

1. Collision frame
   In Random-based access mechanisms, collision frame occurs when two or more nodes try to send data frames over the shared channel simultaneously. The collision causes data frame discarding, which requires a re-transmission. Thus, due to the frame re-transmissions, the energy consumption increases. The authors in [188] showed that in the DFSA mechanism the amount of wasted energy due to the collisions varies from 0.1 to 1000 mJ for different network densities. To alleviate this issue, different approaches such as NOMA [158,163] have been proposed, however, still more researches are required to reduce collision rate and conserve energy.
2. Idle listening
   Although the time listening to the shared medium and waiting to start the frame transmission controls the collision rate, it causes extra energy consumption specifically in random access and hybrid access categories. According to the literature [189], between 80–90% of the energy wastage of data transmission procedure in the distributed mechanisms is related to the idle listening duration. The authors in [155,171,188,190] showed that depending on the network density and mechanism's constraints, energy wastage during idle listening can be varied from 1 mJ to 1 J. Although to balance the trade-off between the idle listening duration and collision rate, different researches have been done [191], finding an optimal value for this duration still remains an open challenge. This issue in the context of duty-cycled mechanisms has a different definition. Based on the data frame transmission in duty-cycled mechanisms, some amount of energy can be wasted, due to idle listening mode. This means a receiver node stays in idle listening mode and waits for receiving a data frame, while no data frame has been sent by the senders.
3. Overhead
   Although control frames do not contain any data, they are necessary for communication management. In random access and controlled access approaches, different QoS requirements, control messages, and long headers within data frames consume extra energy during the transmission procedure. The authors in [192] showed that the energy consumption of the overhead control packets in IEEE 802.15.4 varies from 0.1 to 2 J based on the network density. For these reasons, the overhead reduction issue has been attracting researcher's attention in recent years, and some

solutions such as frame concatenating (superframes) have been proposed to alleviate the overhead issue.

4. Overhearing
   In the case of a dense network, overhearing (i.e., receiving data frames from other transmissions) intensifies and increases the energy consumption of the network. The authors in [180] proposed a decomposition of energy consumption in IEEE 802.11. Since overhearing depends on the size of the network, it changes from 0.01 to 0.11 mJ. According to Section 6 this issue has received less attention rather than collision rate and overhead issues.
5. Hidden terminal
   In random-based access mechanisms, a network may waste energy if two nodes start a transmission at about the same time, but are out of range (hidden) of each other. Based on the number of the hidden nodes, the amount of energy wastage may vary from 1 to 4.3 J [193]. This challenging issue can be reduced through the RTS/CTS mechanism, or even by increasing the power transmission. These two solutions cannot be considered as energy-efficient approaches. For this reason, it is necessary to address this issue in a more energy-efficient manner.
6. Node synchronization
   Although node synchronization approach provides a collision-free data transmission, it is considered the main energy wastage of the channelization MAC protocols [194]. The reason for high energy consumption in this approach is that synchronization requires frequent executions at each node with a defined duration [156]. The amount of wasted energy varies depending on the execution frequency and duration of the synchronization at each node.
7. Unused slots stay idle
   Another issue which causes energy wastage in scheduled-based access mechanisms is the predefined frame slots [156]. Since the specific slot (time/frequency /code/power) is allocated to each node, this slot cannot be used by other nodes to transmit data frames. For this reason, nodes without any data frame to send waste the channel resources (e.g., bandwidth) and energy. The amount of energy wastage may vary based on frame size and network density.
8. Fixed slot-frame length
   Scheduled-based access mechanisms having a fixed slot-frame size, may not have a successful energy-efficient transmission depending on the data frames size. For instance, a long data frame may need to be fragmented to be successfully transmitted. Since the fragmented part of the frame needs additional overhead, it wastes the energy of the network. The authors in [195] showed that in the LPWAN, the transmission energy consumption increases with the number of fragmented frames.
9. Adaptive polling interval to the network load
   This issue reflects the impact of the duration between two successive poll phases in the Polling access method. Although, by increasing the time interval between two poll periods, the number of polls is decreased, and thus the network energy consumption is saved, having long time intervals between these two polling phases increases the energy wastage of the network. Hence, although this issue has been addressed in some researches [37,196,197], finding an equilibrium time interval in polling MAC protocols remains a critical issue.
10. Token pass timing
    In MAC protocols which operate based on the token passing method, the controller node allocates a time interval for passing the token frame to all nodes. During this time interval, no data frame transmission is allowed, and thus, this duration causes energy wastage. Moreover, as the number of network nodes is increased, more energy is wasted due to longer time duration.

7.1.3. Application Diversity

As mentioned in Section 1, IoT systems include a wide range of applications from healthcare and smart cities to industrial automation applications. Nevertheless, each of them requires a different level of KPIs. For instance, healthcare applications require communications with a high level of reliability, availability, and low latency in a small service dimension area with a specific data rate value. Whereas agricultural monitoring must guarantee QoS requirements such as high latency communications, wider service dimension area and lower data rate compared to healthcare applications. Also the reliability in these applications is not as crucial as healthcare applications. The available energy harvesting MAC protocols only focus on one or two KPIs and intend to enhance them for certain applications with a specific range of data rates. Moreover, due to the energy shortage, burstiness of traffic, and lack of synchronization in the network, some real applications may operate based on the new concept of intermittent computing [198]. To specifically address the requirement of intermittent computing in terms of energy consumption, it is necessary to balance the trade-off between these KPIs in the design enhancement of an energy harvesting MAC protocol. The compatibility of these MAC protocols with the diversity of the IoT applications still is a challenging issue.

7.1.4. Adaptation to the Network Conditions

The performance of a wireless network mainly depends on the application type, dynamics of the deploying environment, channel, and MAC layer conditions. These aspects specify the required traffic rate, network density and topology (insertion/removal of the network nodes), the propagation loss, node prioritization, noise interference, channel resource utilization, transmission range, within other parameters [166]. To enhance the design of the MAC protocol, all these parameters need to be taken into consideration. For example, in contrast to the scenarios based on star typologies, the network conditions in multi-hop scenarios dynamically change, and thus, some MAC protocol mechanisms such as channelization-based mechanisms are not suitable for them [160,173]. Another example considers mobility management of the node when a node moves from a network domain with some specific conditions, to another one, and force the network to redefine all its parameters. In this case, the MAC protocol needs to adapt its operation to the new network conditions [194].

7.1.5. Energy Prediction Algorithms

According to Tables 7–10, some of the proposed energy harvesting MAC protocols deploy prediction algorithms such as EWMA, Weather Conditioned Moving Average (WCMA), and Artificial Intelligence (AI) [199] to predict the required amount of energy of the next transmissions, energy harvesting rate, satisfy ENO, and make the unpredictable behavior of the harvested energy sufficient for protocol operations [200]. For instance, Q-learning and self-learning algorithms are deployed in [201,202] respectively, to achieve optimal approach for energy-efficient communications. It is worth mentioning that to make the network perform in an optimal manner, different energy prediction algorithms depend on the various aspects and requirements of the network, need to be applied at all levels of the IoT architecture. Since machine learning or prediction algorithms require a considerable amount of computational resources, implementing them for dense network scenarios can be complex, challenging, and requires further research.

7.1.6. Validation of the Proposed Energy Harvesting MAC Protocols

In Section 6, we observed that most of the proposed MAC protocols are designed based on analytical models. Also, some works are validated through the use of simulations. However, the simulators which are used in these works are mainly custom-based simulators with ideal conditions, hard to compare or reproduce and may not provide reliable results. In contrast to custom-based simulators, packet level simulators such as NS-3, Optimized Network Engineering Tools in C++ (OPNET++), and Objective Modular Network Testbed in C++ (OMNeT++) are capable of modeling the general structure of the networks such as channel condition, physical, MAC and application layers and imitating the real world network conditions. Other than analytical models and simulation approaches, a few of these works extend the validation of their proposed models to the hardware level and test-bed. For instance, the authors in [203] validated their proposed model with the help of the Field Programmable Gate Array (FPGA) platform, solar and RF energy harvesters. Thus a combination of test-beds,(which consider interaction of different levels and components of the real systems to study the behaviour of the whole system), and simulations based on the packet level simulator for validating the energy harvesting MAC protocols, would be a proper method of validation.

7.1.7. Acceptability of the Design of the Proposed Energy Harvesting MAC Protocols

Plenty of novel energy harvesting MAC protocols have been proposed in the literature. However, those protocols closer to already existing standards have more opportunity to be accepted in the industry. For instance, DeepSleep, HE-MAC, and W^{2}P-MAC, protocols are designed based on the IEEE 802.11 standard, and AH-MAC and RF-AASP MAC protocols are designed based on the IEEE 802.15.4 standard. However other novel MAC protocol definitions require changes on the node behaviour, frame exchanges, and complexity of network, which require strong redesigns of existing standards. The reluctance to deploy them may also lie on the backward compatibility of the proposed MAC protocols with existing wireless devices.

7.2. Open Research Challenges

Supporting energy harvesting at MAC layer in currently available wireless technologies can be a promising solution to the energy shortage of IoT end devices. Nevertheless, it may raise new challenges and issues at different levels of IoT systems. In this subsection some of the research challenges that still remain as open issues are highlighted.

1. Radio Resource Management (RRM)
   Radio level management plays a critical role in efficiently scheduling and controlling different radio network parameters which have an indirect impact on the MAC layer operations, and can improve some of the MAC anomalies. RRM can be performed statically to schedule parameters such as frequency and channel allocation, antenna heights, and directions, modulation and channel coding, static handover and energy level of the nodes. Our analysis shows, although different proposed MAC protocols in the literature dynamically adjust the power control level to the data rate [204] or directional antenna [205], they do not enable the integration of energy harvesting with the MAC layer of IoT systems. Thus, presenting RRM algorithms to make the operation of the energy harvesting MAC protocols more efficient would be an attractive research direction (e.g., cross layer approaches).
2. Scalability to dense networks
   Since IoT systems may include a large amount of devices, optimal and scalable network deployment for these systems is required. This means that, by expanding the size of the network, the MAC protocol must keep the network performance at a stable level and satisfy the fairness and QoS among the network. One approach, which addresses the requirements of a dense network is the massive Machine-Type Communication (mMTC). This approach focuses on 5G and Beyond 5G (B5G) technologies and intends to provide reliable and efficient communications while reducing the energy consumption of the network [206]. Although this approach provides the possibility of energy harvesting integration with IoT systems, due to the low level of transmit power, energy transfer (which is one of the methods of energy harvesting technologies) in massive communications with long-distance is not efficient. According to the existing literature that has been studied in this paper, although different assumptions have been taken into consideration to simulate the performance of an energy harvesting MAC protocol in a dense network, optimal deployment of the

nodes (which is an important issue for nodes equipped with energy harvester) and network scalability, has not been studied at the same time.

3. Heterogeneity among IoT systems
In IoT applications such as smart cities, devices may operate based on different technologies and protocols with various constraints and characteristics. In contrast to homogeneous networks, heterogeneous networks face new challenges, such as the coexistence of the technologies [207]. The coexistence issue arises when two or more technologies intend to access the same radio frequency band to complete their communication process. Since coexistence can cause interference in communications, heterogeneous networks are more likely to waste energy [208]. Rather than the interference issue, other factors, such as the network structure complexity and lack of proper resource management, may cause energy waste in heterogeneous networks. Although, one solution to conserve the energy in these networks without degrading the network performance, is to define a universal ENO value for the network, it may be a challenging issue and remains an open research direction.
4. Interoperability among IoT devices
Different applications that belong to an IoT system require various radio interfaces, network structures, and protocols. This diversity among two or more networks which aim to cooperate at different layers is known as interoperablilty and becomes an issue for IoT systems. From MAC layer perspective, since the energy harvesting MAC protocols are responsible for rescheduling the transmissions, timings, and parameters related to the energy level, interoperability may increase the noise, frame loss, resource utilization and energy wastage in the network. Thus, these protocols need to take into account the effect of interoperability, where the standardizing the interactions between networks can lead to new research directions.
5. Towards batteryless networks with intermittent operations
In batteryless systems, the required energy to keep the device powered, is provided through energy harvesters. However, due to the unpredictable behavior of energy harvesters, the system may face failure. This problem, which is also known as intermittent system problem, faces various challenges at different levels of the network. Since the intermittent networks cannot operate based on the traditional communication protocols, they require modifications and adjustments at communication coordination and scheduling based on the intermittent nature of the network. At this level, a robust MAC protocol and network topology are needed to provide energy-aware protocols and satisfy the requirement of the intermittent systems. Although researchers have been attempting to address these challenges, defining a standardization at each level of this system establishes new research directions.
6. Achieving energy efficiency in fog computing
This concept refers to moving an enormous amount of computational data operations, management, and storage from data centers and core networks to the communication level of the IoT, where the central units (gateways and APs) are located, to reduce the computational workload of the data centers [209]. Since big data parallel processing which is the key operation of data centers, is a power hungry operation, artificial intelligence approaches are introduced to alleviate the energy consumption of this process. For instance, machine learning algorithms which are known as artificial intelligence approaches use the information of the end devices and then manage the network resources by adapting the MAC layer (e.g., frame size adjustment) of the central units to the behavior of end devices. Thus, artificial intelligence approaches in Fog computing open new research directions in the energy-efficient IoT paradigm.
7. Hybrid approaches for energy harvesters
Since the energy harvesters that keep IoT systems powered have different harvesting rate, to enable the energy harvesting techniques at the MAC layer, the operations at this layer need to be adjusted to the harvesting rate. The harvesting rate depends on the energy harvester type, environmental conditions and network topology changes.

To tackle the dependency of the harvesting rates on the environmental conditions, network topology changes, and to achieve higher output power, some researchers have intended to integrate different energy harvesters. However, the design of hybrid energy harvester may introduce new challenges. These hybrid harvesters may harvest more energy than the system needs which is wasted through the energy leakage in the energy storage devices. To reduce the extra amount of harvested energy, the energy management needs to match the harvested energy with the energy requirements of the IoT applications.
Alongside this issue, adaptability to different energy harvesting rates may increase the complexity of the MAC protocol, and based on our background study, only a few works deploying hybrid energy harvesters [203]. Thus, hybrid energy harvester deployment and extra harvested energy management are challenges that have not been addressed as much as other issues, which open new directions to researchers.

8. Conclusions

The available energy harvesting technologies cannot continuously power up the IoT devices, which are supported by different wireless communication technologies. To make this integration possible, there is the need to optimize the energy consumption on the wireless communication technologies at different IoT layers. Thus, MAC layer operations, which consume most of the energy budget of wireless communication, are the most relevant candidate for applying energy optimization methods and conserving energy. To justify this argument, we provided a thorough review of the MAC layer operations and different MAC optimization techniques, which some of them are employed in the current IoT wireless communication technologies. Then, based on the informative aspects of the MAC layer operations, we developed a unified approach to systematically analyze energy models for each technology. In addition, we extensively studied the available energy harvesting technologies and their constraints. According to this analysis, we showed that, based on the duty-cycle regulation, simple random access mechanism, low energy consumption, and long-range communications, LPWAN technologies are applicable for different IoT use cases. Moreover, since IEEE 802.11ah is specifically designed for IoT systems, it meets various requirements of these systems, such as long-range and low power consumption communications, with higher data rates. In addition, our research on available energy harvesters concluded that technologies like photo-voltaic panels or thermocouples are applicable to these two wireless communication technologies. For these reasons, LPWAN family and IEEE 802.11ah are two of the promising wireless technologies in IoT systems. Also, this paper has described how the available energy harvesting MAC protocols adapt to the integration of energy harvesting in IoT systems, and gave a precise comparison between these MAC protocols based on energy harvesting-related network parameters. These analysis results demonstrated that ENO condition, which is one of the most energy-related parameters for enabling energy harvesting in IoT systems, is only considered by 23% of the reviewed literature set. Furthermore, hybrid access MAC protocols can be one of the optimal approaches for IoT systems equipped with energy harvesters. Their high adaptation to the energy level of the nodes and acceptable network energy consumption reduction favours their presence in 48% of the analyzed literature. Alongside the hybrid access energy harvesting MAC protocols, cross-layer mechanisms show a remarkable energy consumption reduction of the network. However, due to their high computational complexity, they have not reached maturity and have not shown their successful role in the current technologies yet. These results convey that there is still room for improvement in this area. We believe that this survey paper could shed light on enabling the integration of energy harvesting in the IoT concept and guide researchers to explore the adaptation of future MAC layer protocols to energy harvesting techniques in IoT systems.

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4

Enabling Energy Harvesting-Based Wi-Fi System for an e-Health Application: A MAC Layer Perspective

This chapter includes contributions regarding the integration of EH technologies into dense Wi-Fi networks, which was published as a journal article in *Sensors, MDPI*. It focuses especially on introducing an optimization algorithm in the MAC layer. The algorithm aims to find optimal CW combinations in master and slave cells, minimizing energy consumption while meeting QoS requirements in a restricted environment.

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Article

Enabling Energy Harvesting-Based Wi-Fi System for an e-Health Application: A MAC Layer Perspective

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Abstract: The adverse impacts of using conventional batteries in the Internet of Things (IoT) devices, such as cost-effective maintenance, numerous battery replacements, and environmental hazards, have led to an interest in integrating energy harvesting technology into IoT devices to extend their lifetime and sustainably effectively. However, this requires improvements in different IoT protocol stack layers, especially in the MAC layer, due to its high level of energy consumption. These improvements are essential in critical applications such as IoT medical devices. In this paper, we simulated a dense solar-based energy harvesting Wi-Fi network in an e-Health environment, introducing a new algorithm for energy consumption mitigation while maintaining the required Quality of Service (QoS) for e-Health. In compliance with the upcoming Wi-Fi amendment 802.11be, the Access Point (AP) coordination-based optimization technique is proposed, where an AP can request dynamic resource rescheduling along with its nearby APs, to reduce the network energy consumption through adjustments within the standard MAC protocol. This paper shows that the proposed algorithm, alongside using solar energy harvesting technology, increases the energy efficiency by more than 40% while maintaining the e-Health QoS requirements. We believe this research will open new opportunities in IoT energy harvesting integration, especially in QoS-restricted environments.

Keywords: energy harvesting; e-Healthcare; Wi-Fi technology; MAC layer; optimization; MIoT; contention window; sleep mode; objective function

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1. Introduction

The Internet of Things (IoT) ecosystem includes a massive number of physical devices, which interact through the Internet to improve and enhance various applications and services [1]. According to the Cisco Annual Internet Report [2], by the end of 2023, the number of connected IoT devices will increase to 29.3 billion devices. Thus, conventional batteries, known as the most common energy source for IoT devices, might not be efficient. This inefficiency is due to the limited lifetime of conventional batteries, which require frequent replacement and maintenance. The adversity of battery replacement and maintenance intensifies, especially where the devices are placed in hard-to-reach areas and dangerous places. In addition, the disposal of this amount of batteries releases toxic material into the environment.

Different passive techniques have been introduced in the literature to diminish the disadvantages of conventional batteries and reduce their maintenance cost. One of these techniques is deploying energy harvesting technologies, which is considered a promising solution to provide enough energy for IoT devices and keep them powered up.

Although all IoT sectors benefit from energy harvesting technologies, deploying these technologies in Medical IoT (MIoT or IoMT) offers a double benefit: reducing the maintenance cost and saving human life. This would be especially beneficial in the event of a pandemic, such as the one that occurred in 2020 (the COVID-19 crisis), when hospitals' total capacity was nearly fully occupied by patients who required specialized care [3]. In these cases, establishing a center such as a field hospital or a mobile medical unit is inevitable. Since these constructions face new challenges in providing enough reliable energy sources for the monitoring devices, cooperating energy harvesting technologies (solar cells or Piezoelectric harvesters) can help deliver sustainable and reliable energy sources [4] for these temporary medical centers.

Another critical challenge in mobile unit deployments is selecting relevant wireless communication technologies. Among all the available wireless communication technologies, Wi-Fi is considered to be cost-effective and accessible deployment technology. Moreover, the Institute of Electrical and Electronics Engineers (IEEE)-based Wireless Local Area Network (WLAN) standard [5] has been widely used in different environments and is one of the most successful wireless communication technologies for indoor environments. For instance, in the case of the coexistence of Wi-Fi and Zigbee in indoor environments, since Wi-Fi devices have a shorter Channel Clear Assessment (CCA) time, they have priority over Zigbee devices. In addition, since Zigbee frame transmissions have a longer frame in the air time, they suffer more than Wi-Fi devices from the hidden node problem [6]. Furthermore, IEEE 802.11 introduces amendments such as IEEE 802.11ax [7], IEEE 802.11be (not standardized yet) suitable for dense indoor environments, and IoT networks similar to a mobile medical unit.

Wi-Fi technology offers powerful benefits for deploying in dense indoor environments. However, the issues inherent to traditional Wi-Fi networks could be intensified in these environments. The challenges that dense Wi-Fi networks face can be studied from two perspectives, the physical layer and the MAC layer. One of the immediate issues related to the physical layer is the placement of the APs in the dense network, which causesoverlapping coverage and have a significant effect on the spectrum efficiency and throughput of the network [8]. Regarding the MAC layer perspective, the other issue is channel interference due to the high number of devices, originating due to the contention-based nature of the MAC layer of IEEE 802.11. In these environments, channel interference causes exposed and hidden node problems and increases the collision rate [9,10]. One of the consequences of all these issues is the increase in the systems' energy consumption.

As we highlighted, due to the high energy-consuming nature of MAC layer operations and the challenges that it faces, integrating an energy harvester may not be sufficient to keep the MIoT devices powered up. Therefore, to reach a sustainable MIoT system without degrading the system's performance and maintaining the QoS at a certain level, there is a need to optimize the energy consumption of the Wi-Fi communication technology at the MAC layer and adapt it to the MIoT systems.

To address the integration of energy harvesting technologies within a dense Wi-Fi network, in this paper, we propose an AP coordination-based optimization algorithm (inspired from the AP coordination method under discussion in the upcoming IEEE 802.11be amendment), that supports the QoS requirements for a restricted QoS environment while mitigating the network's energy consumption. Additionally, we implement a sleep/wake-up method, which considerably reduces network energy consumption. The proposed algorithm is evaluated under extensive simulations in a dense Wi-Fi network in a field hospital, where all the devices are equipped with solar cells. To the best of our knowledge, this is the first time the suggested combination of AP coordination-based and sleep/wake-up algorithms has been outlined in the literature to minimize network energy consumption while preserving a specific degree of QoS for a solar-based dense e-Health environment. Furthermore, we propose an innovative objective function used for evaluation proposes. To summarize, this paper includes the following contributions:

- We conduct extensive simulations in the Network Simulator 3 (ns-3) environment, which can accurately mimic the deployment of Wi-Fi communication for solar-based medical devices in the proposed scenario.

- We incorporate the AP coordination idea from the upcoming IEEE 802.11be standard in our AP coordination-based optimization approach, while also maintaining backward compatibility with the IEEE 802.11 standard.
- We propose an objective function based on medical-grade QoS criteria and energy usage.
- We propose a sleep/wake-up mechanism that puts non-AP stations to sleep for a time interval if residual energy falls below a particular threshold. This approach allows network energy consumption reduction while maintaining the desired level of QoS.

The remainder of this paper is organized as follows. In Section 2, the main concepts around the fundamental IEEE 802.11 MAC layer mechanisms and the relevant amendments, energy harvesting technologies, and e-Health applications are introduced. Section 3 highlights the relevant existing works in the literature. In Sections 4 and 5, the applied methodology and all the steps taken for the simulations are explained. Section 6 provides the performance evaluation of the AP coordination-based optimization algorithm, along with an analytical discussion. Finally, in Section 7, some final remarks and future directions are given.

2. Background Study

In this section, we divide the main concepts of this paper into three parts, briefly explain each concept and then find their intersection points. These concepts are listed as electronic healthcare (e-Healthcare), IEEE 802.11 (Wireless communication technology), and the relevant energy harvesting technologies for the e-Healthcare use case.

2.1. E-Healthcare

E-Healthcare refers to the deployment of information and communication technologies (ICTs), such as IoT, cloud computing, big data, and artificial intelligence, to intelligently manage the healthcare system and make it on-demand, more accurate, and more efficient [11–13]. E-Health enables versatile telehealth services (telemedicine, telesurgery, telerehabilitation), wearable devices, e-Health records, smart healthcare applications, etc. These services improve patient monitoring for medical staff and patients, facilitate self-health management, and encourage people to form healthier habits. In addition, e-Health reduces human error and the cost of activities simultaneously.

As explained in the introduction, the growing trend of the MIoT as a subcategory of IoT faces various challenges at different levels of its architecture. As the first level of the MIoT architecture, the sensing and perception layer includes real hardware and is responsible for collecting patients' data. At this level, the devices need to be low-power and low-cost, small in the physical dimension, and user friendly. Since medical sensors have to provide a long operational lifetime, having batteries with a limited lifespan is challenging and motivates the use of low-power consumption devices or even devices without batteries. Removing the battery from MIoT increases the flexibility of wireless devices and the operational lifetime of medical devices, which is especially vital for hard-to-reach devices and reduces maintenance costs.

The second level defines the communication protocols regardless of the use of either wired or wireless communications. At this level, different power management and optimization mechanisms can be applied to satisfy the devices' required low-power consumption feature. In addition, since the content of data transmitted in MIoT is privacy-sensitive, network security features such as confidentiality, integrity, and availability of medical data are challenging. Moreover, since MIoT is considered a QoS-restricted environment, especially in terms of the Packet Loss Ratio (PLR) and delay [14], at this level, ensuring the medical-related QoS requirement is a demanding issue.

The last level is responsible for managing and controlling the applications on devices, which the medical business providers control. Furthermore, some information technologies such as artificial intelligence, deep machine learning for healthcare, and big data belong to this architectural level of MIoT. At this level, the user's privacy is a challenging issue [4,15].

Figure 1 demonstrates a patient who is located in a field hospital and is connected to different medical sensors (the applications which are in red are not considered in the simulation setup), and other real-time applications such as video conferencing with a doctor.

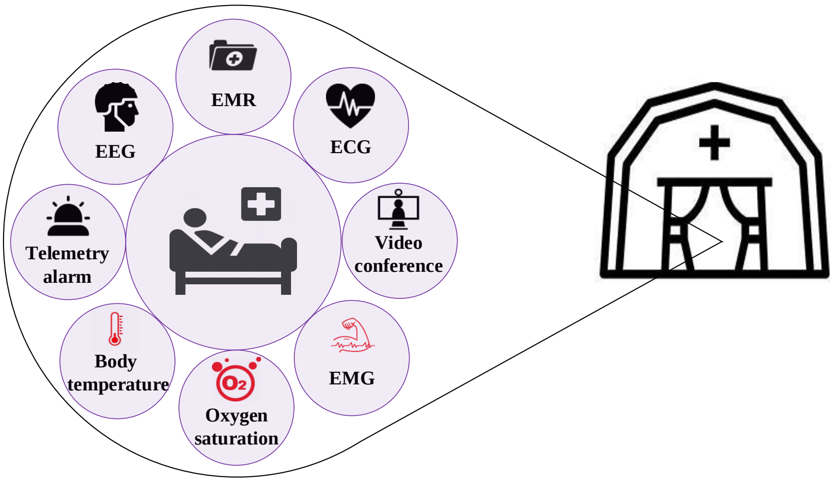


Figure 1. An example of MIoT applications in a field hospital.

2.2. IEEE 802.11

The IEEE 802.11 working group has been standardizing different amendments by specifying various sets of MAC and physical layers for WLAN communications.

The fundamental mechanism of the MAC layer in IEEE 802.11 standard is known as the Distributed Coordination Function (DCF). It uses a Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) method with binary exponential back-off. Figure 2 demonstrates the default access technique known as a two-way handshaking scheme. According to CSMA/CA mechanism, stations monitor the channel before sending the data frame. They will start a back-off countdown if they sense the channel idle for a specific time interval known as Distributed Inter-Frame Space (DIFS). Otherwise, if the channel is sensed as busy, the stations keep monitoring the channel until the channel is sensed idle for a DIFS. Then, the back-off countdown timer starts after the channel is sensed idle for a DIFS. Since DCF is defined in a discrete-time back-off manner, each transmission must begin at the start of the time slot.

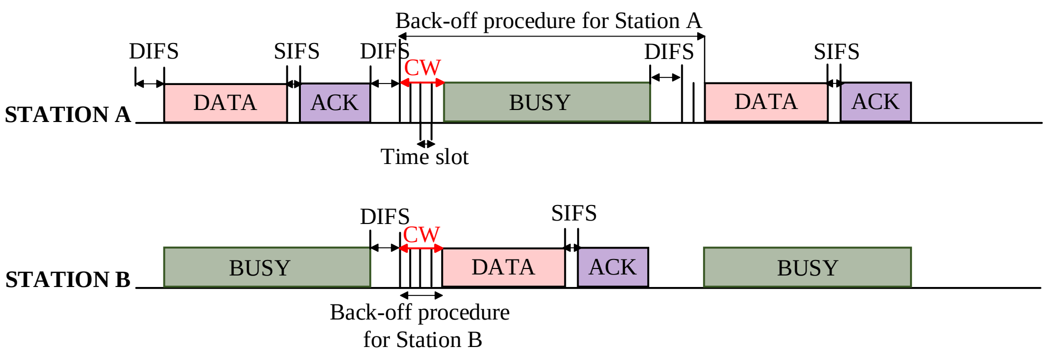


Figure 2. CSMA/CA Back-off procedure.

The back-off procedure is started by initializing the Contention Window (CW) to CW_{min}, where the station chooses a random number within (0, CW-1). The counter decreases the back-off timer if the channel is sensed idle during a time slot. However, in the case of data frame transmission, the timer halts and only reactivates if the channel stays idle for more than DIFS. If the data frame is unsuccessful, the CW is doubled until it reaches its maximum value ($2^n CW_{min} = CW_{max}$). Once a data frame is transmitted, the sender waits for an Acknowledgment (ACK) frame to confirm the data frame's correct reception.

Suppose the station that started the transmission does not receive an ACK frame during the ACK timeout period. In that case, it understands that a collision happened. Therefore, the station retransmits the data frame according to the back-off process. The data frame will be discarded if it experiences more collisions than the maximum retry limit.

The IEEE 802.11 standard group defines another mechanism known as Enhanced Distributed Channel Access (EDCA), which supports differentiated Quality of Service (QoS) in Wi-Fi communications. This mechanism introduces four different Access Categories (AC_{VO}, AC_{VI}, AC_{BE}, and AC_{BK}) to prioritize channel access, where the AC_{VO} has the highest priority and AC_{BK} has the lowest priority. The AC_{VO}, AC_{VI}, AC_{BE}, and AC_{BK} categories are meant for voice, video, best-effort, and background traffic. According to this mechanism, the MAC layer parameters such as CW_{min} and CW_{max}, Arbitrary Inter-Frame Space (AIFS), Transmission Opportunity (TXOP), and queue length are set to different values to achieve this prioritization. For instance, AC_{VO} parameters are assigned to the smallest values among other categories to give the highest transmission opportunity to the traffic under this category. However, since different applications require various ACs, and Wi-Fi proposed fixed EDCA parameters for each AC (Table 1), it is unsuitable and unfeasible for heterogeneous networks [16], such as e-Health networks, where the time-sensitive and emergency traffic require a certain level of QoS. For this reason, new ACs with special queues are required. Moreover, as we explained, since the CW is the principal parameter of the back-off procedure, among the EDCA-related parameters [17], which are listed in Table 1, CW has the most impact on rescheduling the transmissions and QoS parameters.

Table 1. Default EDCA ACs parameters.

Access Category	CW_{min}	CW_{max}	AIFSN	TXOP
VO	7	15	2	1.5 ms
VI	15	31	2	3.0 ms
BE	31	1023	3	0.0 ms
BK	31	1023	7	0.0 ms

As highlighted in previous works [18–20], since the inherent behavior of DCF and EDCA mechanisms are contention-based, collisions may be caused by simultaneous transmissions, which is one of the reasons that imposes extra energy consumption on the Wi-Fi stations. It is worth mentioning that, in Time Division Multiple Access (TDMA), a control channel makes the channel collision-free; however, this feature is not available on Wi-Fi. The other reason behind the energy-hungry feature of the DCF mechanism is the transmission errors due to the imperfect channel condition, which causes re-transmission. Besides the amount of energy consumed in the transmission state, the idle state of DCF can also consume a significant amount of energy. Although various methods have been introduced to reduce these effects, they need to precisely select the involved parameters to avoid extra energy consumption [21]. For instance, setting the beacon and idle intervals in the power-saving mode is very important to prevent frequent wake-up nodes or simultaneous wake-ups from wasting the station's energy.

2.2.1. Previous IEEE 802.11 Amendments

The IEEE 802.11 standard group introduced different features to the amendments to meet the IoT requirements while reducing the energy consumption of the MAC layer operations. For instance, IEEE 802.11ah [22] provides some additional features to the MAC layer of IEEE 802.11, such as hierarchical Association IDentifiers (AID), group sectorization, Restricted Access Window (RAW), Relay AP, bi-directional TXOP, and Target Wake Time (TWT) [23], that make this amendment enable supporting the IoT concept. However, IEEE 802.11ax and IEEE 802.11ba [24] were designed to support dense and low-power consumption deployments, respectively. The Basic Service Set (BSS) coloring MAC feature in IEEE 802.11ax makes this amendment suitable for dense network deployment [9]. Furthermore, the energy efficiency is provided through microsleep, TWT, and Opportunistic Power Save (OPS) mechanisms [25]. In contrast to these two amendments, IEEE 802.11ba balances the trade-off between low-power consumption and latency by implementing the concept of Wake Up Radio (WUR) [26].

2.2.2. Wi-Fi 7

Along with the aforementioned IEEE 802.11 amendments, an upcoming IEEE 802.11be has features that IoT systems can benefit from them. The IEEE 802.11be is built on top of the IEEE 802.11ax amendment and will support real-time applications, where QoS provisioning is challenging. In addition, this amendment will provide a very high data rate and makes massive Multi-Input Multi-Output (MIMO) communications possible. Some advanced modifications and enhancements are introduced at the Physical (PHY) and MAC layers to fulfill these features. For instance, the AP coordination and Hybrid Automatic Repeat Request (HARQ) are presented at the MAC layer. According to the AP coordination technique, so-called master APs, to improve the performance of their associated non-AP stations, have the ability to communicate with other APs located within its transmission range (slave APs), where the master AP receives the beacon frames the slave APs. In this technique, the master AP is able to dynamically request the slave APs to reschedule the resources based on the channel conditions (cf. Figure 3) [27]. It is worth mentioning that this technique is specifically designed for the needs of uncoordinated systems; however, the coordinated systems can benefit from the concept of this technique. Moreover, the HARQ technique combines the forward error correction method and ARQ to deliver reliability for data frame transmission. Furthermore, the pick rate, channelization, and time planning at the PHY layer are improved [28,29].

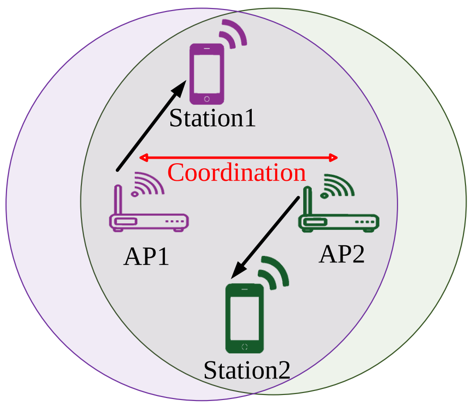


Figure 3. Wi-Fi 7 allows AP coordination.

2.3. *Energy Harvesting in E-Healthcare*

MIoT can benefit from different types of harvesting technologies to keep power-up MIoT devices and introduce battery-less devices [30–33]. Among the existing energy harvesting mechanisms, photo-voltaic, piezoelectric, Thermoelectric Generator (TEG), and Radio Frequency (RF) are the most relevant technologies for the MIoT [34,35].

Photo-voltaic cells absorb the energy from artificial light or sunlight and then converts it to electric energy. Based on the amount of light radiation, the power density of the cell varies from 10 $\mu W/cm^3$ to 100 mW/cm^3 [4].

A rectenna or RF harvester captures the RF signals (dedicated or radiated signals), and then the rectifier circuit (peak detector and voltage elevator) converts them to DC signals. Depending on the physical features and position of the Wireless Energy Harvester (WEH), the power density of RF harvesters varies from 0.1 $\mu W/cm^2$ to 300 $\mu W/cm^2$ [4].

TEG or thermocouple captures the generated voltage based on the temperature difference between the two types of metals or semiconductors. Various types of the TEG provide a wide range of power density from 40 $\mu W/cm^2$ to 50 mW/cm^2.

A piezoelectric energy harvester obtains energy from a crystal-ionized piezoelectric material under a certain strain (human motion and activity). This harvester converts kinetic energy to electric energy. Depending on the harvester material and the amount of kinetic energy, the piezoelectric power density varies from 0.021 $\mu W/mm^3$ to 2 W/cm^3 [4].

Due to the high power density of solar cells and piezoelectric harvesters and their form factor flexibility, these harvesters are widely used in IoT applications [4]. However, in MIoT systems, since TEG and piezoelectric harvesters are able to harvest energy from the human body, they attract much attention from industry and academia. The aforementioned energy harvesters are summarized in Table 2.

Table 2. Relevant energy harvesting for MIoT system [4].

Energy Source	Energy Harvester	Power Density
Sun radiation Artificial light	Photo-voltaic cell	10 $\mu W/cm^3$ 100 mW/cm^3
Radio Frequency	Wireless energy harvester	0.1 $\mu W/cm^2$ 300 $\mu W/cm^2$
Heat	Thermocouple	40 $\mu W/cm^2$ 50 mW/cm^2
Human body motion Vibration	Piezoelectric	0.021 $\mu W/mm^3$ 2 W/cm^3

Figure 4 represents the relevant energy harvesting technologies that can be implemented in an e-Healthcare sector based on the positions and activities of the patient. The possible positions on the human body for each energy harvester are determined by a number corresponding to that specific energy harvester technology. For instance, a kinetic-based energy harvester (piezoelectric) is able to harvest energy from the movement of the ankle, finger, or foot of a person, while a vibration-based energy harvester can be placed on the chest or elbow of the person. These points are depicted as numbers 3 and 4 [36] in Figure 4, respectively. Since the photo-voltaic panel needs to be in contact with artificial light or sunlight radiation, the most suitable position for this energy harvester is the forehead of the person (number 1) [37]. Although the WEH does not need a direct connection to the wireless waves, one of the suitable positions for its placement is on the shoulder of the person (number 5) [38]. Finally, the wrist of the person can be a proper position for TEG harvester placement. Since in the wrist measuring the temperature difference between the human body and the air can be more feasible (number 2) [39].

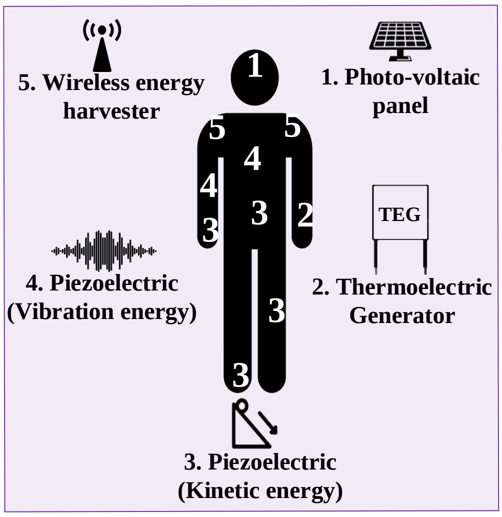


Figure 4. An example of the energy harvesters placement on the human body in the MIoT system.

3. Related Work

In recent years, IEEE 802.11 WLAN has been one of the attractive wireless technologies deployed in IoT networks. However, due to the high interference nature of its medium and high energy-consuming MAC layer operations, deploying an energy harvesting technology to extend the lifetime of the IoT devices while ensuring QoS features becomes a challenging issue. This issue becomes more demanding for QoS-restricted environments, where real-time, multimedia and distributed emergency applications are deployed, such as the healthcare sector, disaster recovery, and industrial emergency traffic. Although there have been many works in the literature on QoS requirements provisioning, they do not consider the requirements of energy harvesting technology deployment aligned with the QoS guarantee as a critical point in the IEEE 802.11 WLAN. Thus, to completely understand this issue, there is a need to have a structural literature review of MAC layer modifications to provisioning QoS and the integration of energy harvesting technologies with the IEEE 802.11 standard. This section will explain the related works regarding these perspectives.

3.1. MAC Layer Modification

In this subsection, we explain the relevant studies on MAC modification and enhancement to meet the QoS requirements within the IEEE 802.11 standard.

In 2005, the IEEE 802.11e working group introduced the IEEE 802.11e amendment, whose MAC layer supports time-sensitive applications [17]. However, the EDCA mechanism in this amendment has limitations and does not support QoS-restricted environments. One of the studies on enhancing IEEE 802.11e QoS is proposed in [40]. In this work, the authors consider three types of traffic, real-time medical traffic such as Electrocardiogram (ECG), emergency alarms, and non-real-time traffic. The authors assign different levels of priority to these applications. Then, based on the QoS requirements and the level of priority of each medical application, they introduce an adaptive AIFS algorithm for each medical traffic. In this algorithm, the station with the higher priority traffic maintains the required QoS level by requesting the stations with lower priority traffic to increase their AIFS values and delay their transmissions. In addition, they propose an admission control algorithm, which is able to guarantee the QoS for the highest priority traffic. Although the authors show that the proposed algorithms perform well under saturated conditions where more stations join the network, the QoS may not be guaranteed.

As we explained in Section 1, compared to the AIFSN parameter, the CW value is another MAC layer parameter that has a more significant impact on the network performance metrics such as the end-to-end delay, throughput, PLR, collision rate, and even energy consumption of the network. For this reason, extensive research has been conducted on CW value variations to address QoS restrictions. In some works, the CW size is fixed at an optimal value. In contrast, in some other research, the CW size is dynamically adapted to an optimal value regarding the network conditions. Tian et al. in [41] proposed an algorithm based on the CW value doubling not only when a collision occurs but also when the channel is sensed as busy. By doubling the CW value, the stations which suffer from overhearing can benefit more by reducing their collision rate. However, the stations with less overhearing will face longer end-to-end delay. In contrast to the previous work, to mitigate the long delay, Syed et al. in [42] proposed a dynamic CW adaptation based on the network load. The proposed algorithm estimates the number of active stations to reduce the number of retransmissions due to the high collision rate in high traffic load conditions. Then it selects the most proper CW value based on that estimation for each access category. Thus, for a dense network, a higher value of CW is determined, and a lower CW value is specified for lower traffic loads. Therefore, this algorithm improves the throughput and collision rate for the delay-sensitive application while minimizing the delay of the network. However, in these studies, the energy efficiency of the network was not considered.

Accompanied by the AIFS and CW dynamic adaptations, in the IEEE 802.11ah amendment, the QoS can be guaranteed through the RAW feature. However, this approach has not received much attention. The authors in [43] assign different channel access timing for each group of stations based on the priority of their QoS requirements. For this reason, they define two types of stations, stations with periodic traffic and stations with non-periodic traffic. In the case of frame collision, the periodic stations halt the transmission procedure, and only non-periodic ones continue to transmit. Based on this algorithm, the stations with higher priority have more chance to access the channel than stations with lower priority. This means that the QoS in the stations with the lower priority may not be guaranteed. In another QoS provisioning study, the authors mathematically model the EDCA concept into the RAW feature of IEEE 802.11ah [44]. This algorithm performs station categorization based on the back-off value, the idle state probability, and the throughput during the non-idle states. However, according to the proposed algorithm, although QoS is guaranteed in scenarios with a low traffic load, the stations with lower priority will suffer from long delay and low throughput. To address this issue, the authors in [45] introduce a longer RAW size for stations with higher priority compared to the lower priority stations. Nevertheless, the proposed algorithm is not completely backward-compatible with IEEE802.11ah due to its back-off procedure.

One of the latest IEEE 802.11 amendments, known as IEEE 802.11ax, improves the concept of multi-user transmission by introducing Orthogonal Frequency-Division Multiple Access (OFDMA). This feature makes channel scheduling and resource allocation flexible for high-density networks. In [46], an efficient channel scheduler is implemented in the AP, which is able to increase the resource unit allocation. The algorithm makes the decision based on the amount of data and the information priority of the QoS in each associated station. Therefore, the proposed algorithm provides the QoS requirements in dense networks.

In recent years, with the advent of the concept of artificial intelligence, researchers have tried to benefit from different machine learning methods in the e-health sector to improve the performance of the healthcare systems, such as telehealth monitoring and remote patient monitoring. Malche et al. [47] propose a machine learning method for a MIoT device that performs real-time monitoring of the vital signal of the patient during specific activities such as walking, running, exercising, and sleeping. Although the wireless communication technology in this work is considered Bluetooth Low Energy (BLE), their work could be adapted by including the concept of master-slave communication. In addition, the sleep/wake-up method and the integration of an energy harvester can be introduced to the network. The authors in [48] propose a machine learning approach to predict the patient's health status in real time by monitoring vital signals. However, the role of energy harvesters and methods to reduce the network's energy consumption have not been taken into consideration.

3.2. *Integration of the Energy Harvesting Technologies with Wi-Fi*

Comprehending the current research on MAC layer modifications for QoS-restricted environments demonstrates that the MAC layer operations may consume more energy under these conditions. In addition, applying machine learning methods increases the computational complexity of the systems, and the devices' energy consumption rises in consequence. In these cases, integrating energy harvesting techniques becomes essential. Thus, there is a need to study the integration of these technologies within the IEEE 802.11 standard. This study will lead us to elaborate on the existing gap in the literature.

One of the earliest investigations on the integration of energy harvesting technologies within the IEEE 802.11 standard is proposed in [49]. In this work, a CO_2 sensor that communicates based on the IEEE 802.11 standard is powered up with indoor light radiation. Although the authors demonstrate the possibility of sustainable wireless communication, they do not consider energy efficiency in their experiments. They claim that the consumed energy can be reduced to half of the current value by applying an energy-efficient MAC layer protocol. The authors in [50] proposed an algorithm based on the 802.11 power-saving mechanism, which offers more priority to the stations with a lower level of energy. Each ambient energy-based station is frequently sent to the sleep mode to save energy in this algorithm. Although the proposed algorithm reduces the overhearing issue, it suffers from a long delay due to random sleep duration and wake-up modes.

Among all energy harvesting technologies, since RF harvesters can directly harvest Wi-Fi signals from nearby Wi-Fi devices, the integration of the RF harvesters with IEEE 802.11 has attracted more attention in academia and industry. For instance, in [51], the authors design, optimize and fabricate a rectenna, which is able to harvest energy from the 2.4 Ghz frequency band from Wi-Fi devices. Based on the simulation and experimental results, they demonstrate that the proposed rectenna is low-cost and easy to integrate with IoT devices. One of the latest investigations on RF harvester use in WLAN scenarios is presented in [52], in which the wake-up receiver and duty cycle concepts are combined to address the energy efficiency issue in IEEE 802.11-based communications. This work demonstrates the feasibility and flexibility of the wake-up signal to reduce the energy consumption of the uplink and downlink wireless communications. The authors claim that the proposed approach outperforms the IEEE 802.11 power-saving mechanism and can be further deployed in batteryless IoT devices.

3.3. Energy Harvesting MAC Layer Protocols

In addition to the works mentioned previously, there are studies in the literature on energy harvesting MAC protocols, in which the authors proposed MAC mechanisms to reduce energy consumption by balancing the trade-off between collision rate and overhead reduction, QoS provisioning, or idle listening duration. For instance, the authors in [53] provide channel prioritization based on the content of a frame while adjusting the wake-up duration to the energy level of an individual node to reduce the energy consumption of the network. The shortcoming of this method is its random back-off procedure, where nodes waste a considerable amount of energy during the long idle listening. Another QoS MAC protocol which is defined in [54], provides four different data prioritization. In this mechanism, transmissions are organized by the receiver based on each node's waiting time, duration, and energy level. As with the previous research, the prioritization in this protocol is determined by the frame contents of each node. This protocol reduces the delay of the networks with dynamic traffic load. However, this protocol may face a long delay in applications with a high collision rate and waste the energy of the network. The first work deploys a generic energy harvester, whereas the second study integrates a solar panel to the sensor nodes. The MAC mechanisms, which are specifically designed for Radio Frequency energy harvester, are proposed in [55–57], where the prioritization of the frame transmissions are scheduled based on the residual energy, energy harvesting rate, or Energy Request frame (ER) of the stations. However, since these works revamp the structure of the CSMA/CA mechanism, the compatibility and adaptability of these MAC mechanisms with the IEEE 802.11 becomes a problem and requires an accurate justification [55]. Moreover, the key role of the QoS metrics provisioning is clearly defined in works such as [53,54]. In addition, integrating the energy harvesters with MAC mechanisms in these works may not lead to the reduction of energy consumption of the network.

According to the available state-of-the-art, although some simulators such as QualNet, Cooja, ns-2, and MATLAB have been widely used in IoT network simulations for analytical analysis, the energy models reveal different limitations. For instance, these models for energy harvesting systems are abstract and straightforward and do not address many energy harvesting technologies and process features. However, since the defined energy model in ns-3 is an accurate model [58], it is able to provide a simulation environment that addresses these constraints accurately. In addition, it has the ability to enable real applications through Direct Code Execution and packet sending over actual Network Interface Cards (NICs) to testbeds.

Furthermore, the impact of using energy harvesting technologies on the network's energy consumption and QoS-restricted environments has not been thoroughly studied. Thus, in this paper, we fill this gap in the literature by applying an AP coordination optimization in a solar-based dense Wi-Fi network in the ns-3 environment. Then we introduce a sleep/wake-up duration to reduce the network's energy consumption while maintaining the QoS metrics such as delay and PLR. Finally, we demonstrate the feasibility and energy efficiency of integrating solar energy harvesting technology in a dense medical Wi-Fi network for medical-grade QoS IoT applications based on extensive simulations and the proposed objective function. Table 3 emphasizes the originality of the proposed work by comparing it with relevant previous works.

Table 3. Features comparison of related work and our proposal.

Studies \ Properties	Wireless Communication [1]	MAC Modification	AP Coordination	Sleep/Wake-Up Deployment	Energy Harvester	QoS Support	Dense Deployment
Son et al. [40]	Wi-Fi	✓	✗	✗	✗	✓	✗
Tian et al. [41]	Wi-Fi	✓	✗	✗	✗	✓	✗
Syed et al. [42]	Wi-Fi	✓	✗	✗	✗	✓	✓
Ahmed et al. [43]	Wi-Fi	✓	✗	✓	✗	✓	✓
Ali. et al. [44]	Wi-Fi	✓	✗	✓	✗	✓	✓
Ali. et al. [45]	Wi-Fi	✓	✗	✗	✗	✓	✓
Filoso et al. [46]	Wi-Fi	✓	✗	✗	✗	✓	✓
Malche et al. [47]	BLE	✗	✗	✓	✗	✗	✓
Sheela et al. [48]	Wi-Fi	✗	✗	✗	✗	✗	✓
Fafoutis et al. [49]	Wi-Fi	✓	✗	✓	✓	✗	✗
Lin et al. [50]	Wi-Fi	✓	✗	✓	✓	✗	✓
Shafique et al. [51]	Wi-Fi	✗	✗	✗	✓	✗	✓
Blobel et al. [52]	Wi-Fi	✓	✗	✓	✓	✗	✓
Kim et al. [53]	Multiple	✓	✗	✓	✓	✓	✗
Sarang et al. [54]	Multiple	✓	✗	✓	✓	✓	✗
Kim et al. [56]	Multiple	✓	✗	✗	✓	✗	✓
Naderi et al. [55]	Multiple	✓	✗	✗	✓	✗	✗
Guntupalli et al. [57]	Multiple	✓	✗	✓	✓	✗	✓
Our proposal	Wi-Fi	✓	✓	✓	✓	✓	✓

[1] In multiple studies the focus of the authors is on the CSMA/CA as the channel access mechanism. Since this mechanism can be used in different wireless communication technologies such as Wi-Fi, Zigbee, LoRa (class C devices), and active RFID, we convey it as multiple wireless communication technologies.

4. Methodology

In this section, first we define the implementation of the proposed optimization algorithm and sleep/wake-up mode in ns-3. Then we describe the structural layout of a station in this simulator, and finally, we explain the network evaluation parameters based on their respective expressions.

4.1. AP Coordination-Based Optimization Algorithm

In this subsection, first we express the method that we define to find the combination of CW_{min} and CW_{max} for each AC, then we explain the functionality of the proposed algorithm in detail.

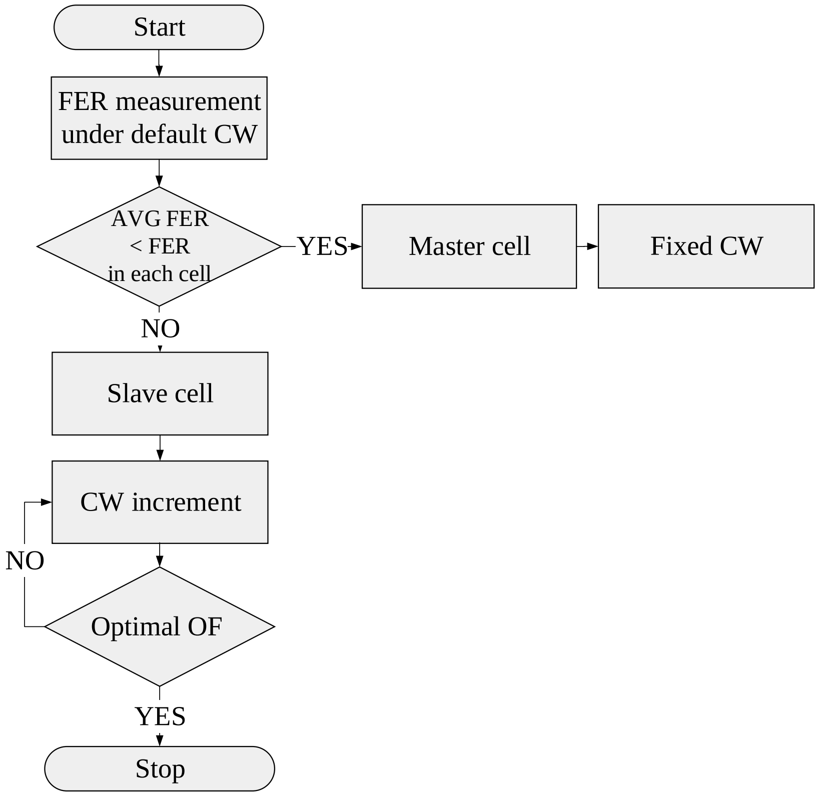
$$CW_{\text{max-new}} = CW_{\text{min}} + \alpha \tag{1}$$

Equation (1) demonstrates the method to obtain the new CW_{max} values. In our approach, the relation between CW_{max} and CW_{min} maintains the same as the DCF mechanism which is given by $CW_{max}= 2^{n}CW_{min}$. However, we add an initial value as α to this relation to increase the buffer slightly. In this Equation, α is the difference between the standard CW_{min} and CW_{max} values and defines the CW size. The α value is defined as 8, 16, and 922 for AC_{VO}, AC_{VI} and AC_{BE}, respectively. According to this method, the CW changes are adapted to the traffic while maintaining the CW size constant defined in the IEEE 802.11 standard Table 1.

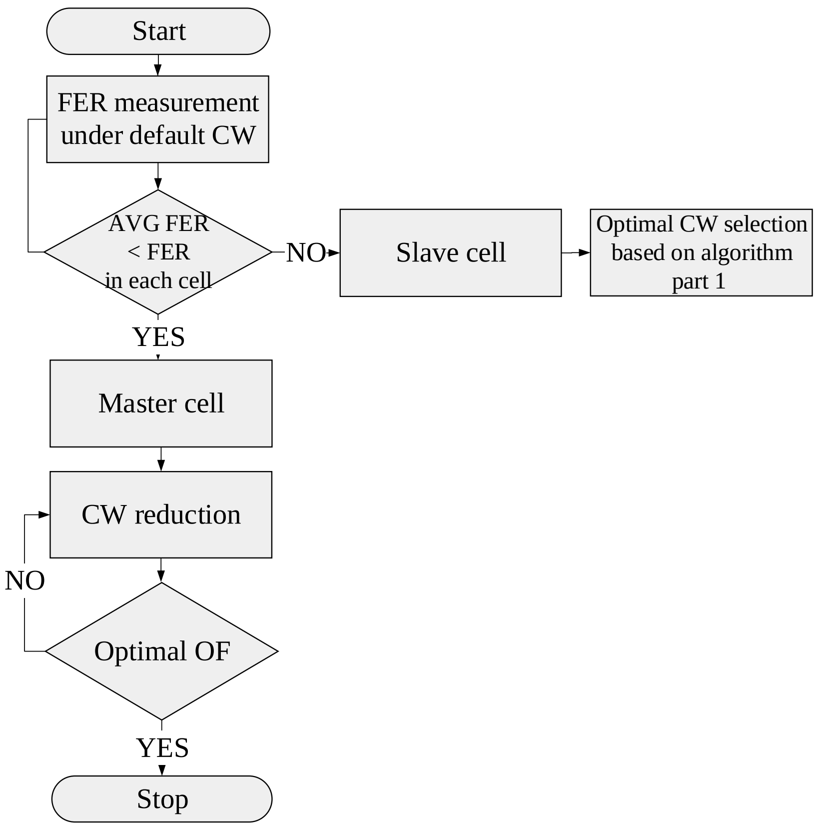
As explained in Section 2, in the AP coordination technique, the master APs have the possibility to communicate with slave APs to reschedule their resource allocation. This technique addresses the QoS requirements for QoS-restricted applications, particularly for real-time, multimedia, and emergency applications. Our proposed AP coordination-based optimized algorithm, divided into two main parts, is retrieved from this technique to meet the medical-grade QoS requirements while adapting energy harvesting technology in the IEEE 802.11-based network.

As the preliminary step to the algorithm, the CW is changed in all the cells to find the optimal CW combination for the network. The CW optimal value for each desired medical application is selected based on the level of QoS parameters and energy consumption per cell. Then the procedure of the algorithm starts by dividing the APs into two groups based on the Frame Error Rate (FER) per cell obtained values when the CW values are set to the standard values. The cells with a greater FER value than the average FER per cell are labeled as master cells; otherwise, they are labeled as slave cells. In the next phase, the CW values of master cells are assigned to the optimal CW values, which are obtained in the preliminary step, and the algorithm increases the CW values for slave cells according to Equation (1). For each set of CW combinations, the QoS parameters such as delay, PLR, and FER are analyzed, and if they meet the medical-grade QoS requirements, the algorithm will stop. Otherwise, the phase where the CW values are increased will repeat until these metrics meet the requirements. The flow graph in Figure 5a illustrates each stage of the procedure of the algorithm.

The second process of the algorithm, which is demonstrated in Figure 5b, starts by dividing the cells into two groups of master and slave cells, as explained in algorithm part 1. However, at this point, CW values are kept constant at the optimal CW values, which are obtained based on part 1, and the CW values on master cells shrink by a non-standard value gradually. In the end, for each set of CW combinations, the desired QoS parameters are analyzed. If they only meet the medical-grade QoS requirements, the algorithm will stop; otherwise, the phase where the CW values are decreased will repeat until these metrics meet the requirements.



(**a**) Algorithm part 1



(**b**) Algorithm part 2

Figure 5. Flow graph of the AP coordination based optimization algorithm.

4.2. Sleep/Wake-Up Mode

Additionally, we introduce a sleep/wake-up technique in the network. When the remaining energy of the network drops below a certain level, this method is triggered. It would considerably reduce the energy consumption of the non-AP stations associated with both slave and master APs while having a negligible impact on medical-grade QoS requirements. However, the greatest benefits are for the master cells, that otherwise had increased FER, which resulted in more energy being consumed in collisions. The schematic of this technique is illustrated in Figure 6.

We multiply the offered load by a factor of X (let us say 2, cf. Figure 6b). To transmit the same data along with the addition of the systematic sleep procedure, the wake-up duration and sleep duration for master cells are divided by the same factor X in a manner that the master can only transmit from A seconds to 1/X seconds (e.g., 0 to 0.5 s) and sleep from 1/X to 1/X + 1/X seconds (i.g., 0.5 to 1 s, cf. Figure 6c). Consequently, the slave is only allowed to transmit when the master is in sleep mode (i.g., 0.5 to 1 s). Since each second of transmission is specifically divided base on master and slave cells, A would be continuous with time. Furthermore, the designed algorithm is generic enough to have more than one set of master and slave cells (i.e., if X is 4, then two sets of Masters and Slaves could be used).

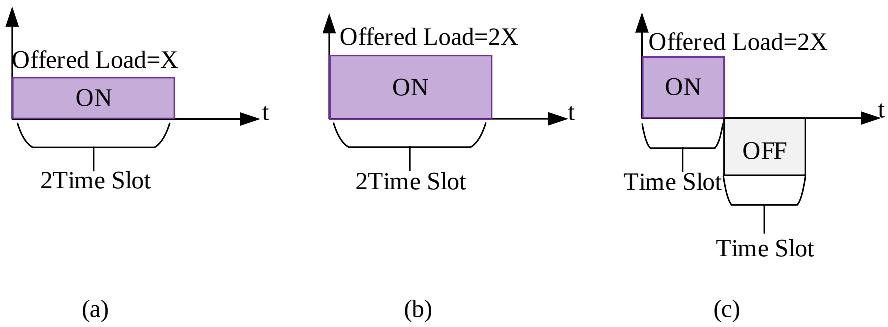


Figure 6. Sleep/Wake-up mode schematic. (**a**) Transmission before applying the sleep/wake-up technique, (**b**) offered load multiplication by factor X, (**c**) wake-up and sleep duration division by same factor X.

The proposed sleep/wake-up mode concept is adapted from the assertion that unnecessary wake-up duration is reduced by forcing a non-AP station to sleep according to its periodicity. According to this technique, the non-AP stations are set to partitions based on the BSS. Then, within each group, the AP has the permission to define a sleep/wake-up duration for each non-AP station to control their access to the channel and reduce the contention on the medium [59].

In accordance with the proposed sleep/wake-up algorithm, in the first stage, when all the cells are in sleep mode, the data rate needs to multiply by the factor of X and time slot is divided by the factor of X, and the counter is initialized. In the next step, if the cell is selected as a master cell, it operates from A second to 1/X seconds (when the counter is an odd value) and is then sent to the sleep mode from 1/X seconds to 1/X + 1/X seconds (when the counter is an even value). In the case of the slave cell, the sleep duration corresponds to the master cell's wake-up duration. This procedure continues until the algorithm's counter reaches the total simulation time, and it will stop. The flow graph of the proposed sleep/wake-up method is illustrated in Figure 7.

Despite the fact that the defined sleep/wake-up method aims to reduce the network's energy consumption, it mimics and addresses the intermittent communications challenge in the Wi-Fi environment. Intermittent communication becomes challenging in the bursty channel with a high level of interference or when there is not enough energy to keep the system powered up, where interruptions in communication are possible.

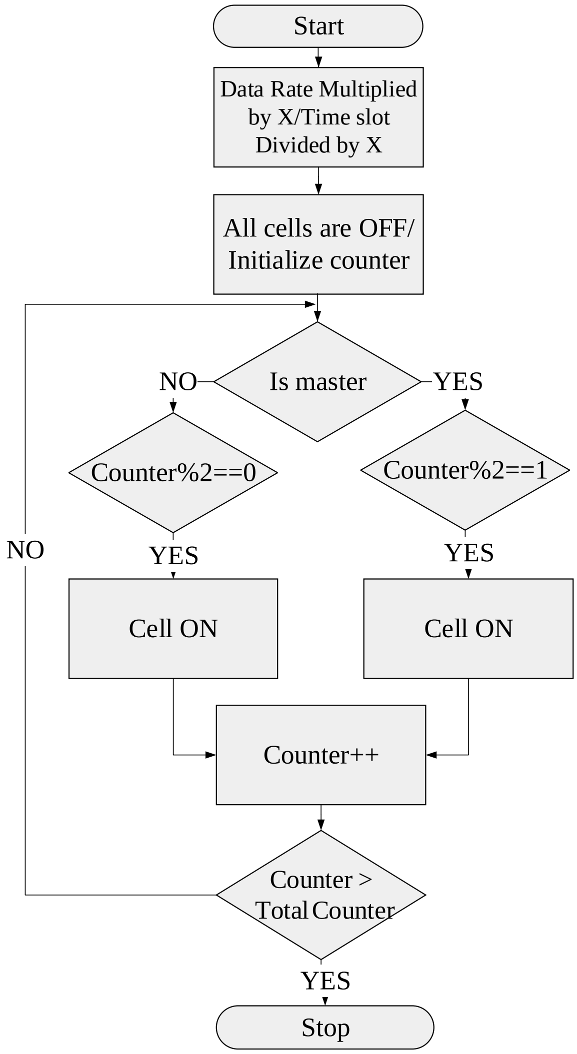


Figure 7. Flow graph of the Sleep/Wake-up mode algorithm.

4.3. System Model

The structure of the ns-3 sensor node (non-AP station) is illustrated in Figure 8, in which different layers of IoT protocol stack along with energy-related modules are presented. As shown in this figure, our studies focus on the PHY layer, MAC layer, and energy-related modules illustrated in color. In contrast, the other layers of the IoT protocol stack, such as the network, transportation, and application layers, including the channel and mobility models, are in grayscale, meaning no changes are applied in this work.

The PHY layer, which is shown in pink, sets different transmission states of communication and the sleep/wake-up state for each station. The MAC layer presented in green is responsible for adjusting the EDCA values for each category, where our AP coordination technique is introduced. The energy-related modules illustrated in purple consist of three main parts: device energy model, Wi-Fi radio energy model, and energy source. The energy source considers different batteries, such as an RV battery, Li-ion battery, or even a capacitor. In addition, this module is responsible for setting the specific parameters for each type of energy source. The Wi-Fi radio energy module defines the consumed energy in each transmission state. Furthermore, it is responsible for calculating the network's total energy consumption. In addition, the Wi-Fi radio energy module is installed on each station through the device energy model [60]. Apart from these modules, there is a solar energy harvester, which is designed for ns-3 [58]. However, this module does not exist in the official ns-3 versions. The ns-3 solar harvesting system is an accurate model which considers different aspects of the harvesting process. This system realistically designs a solar panel and mathematically models various characteristics of the sun, which have an impact on harvesting the energy. The actual amount of power that a solar panel harvests from sun radiation at a given time is obtained through Equation (2).

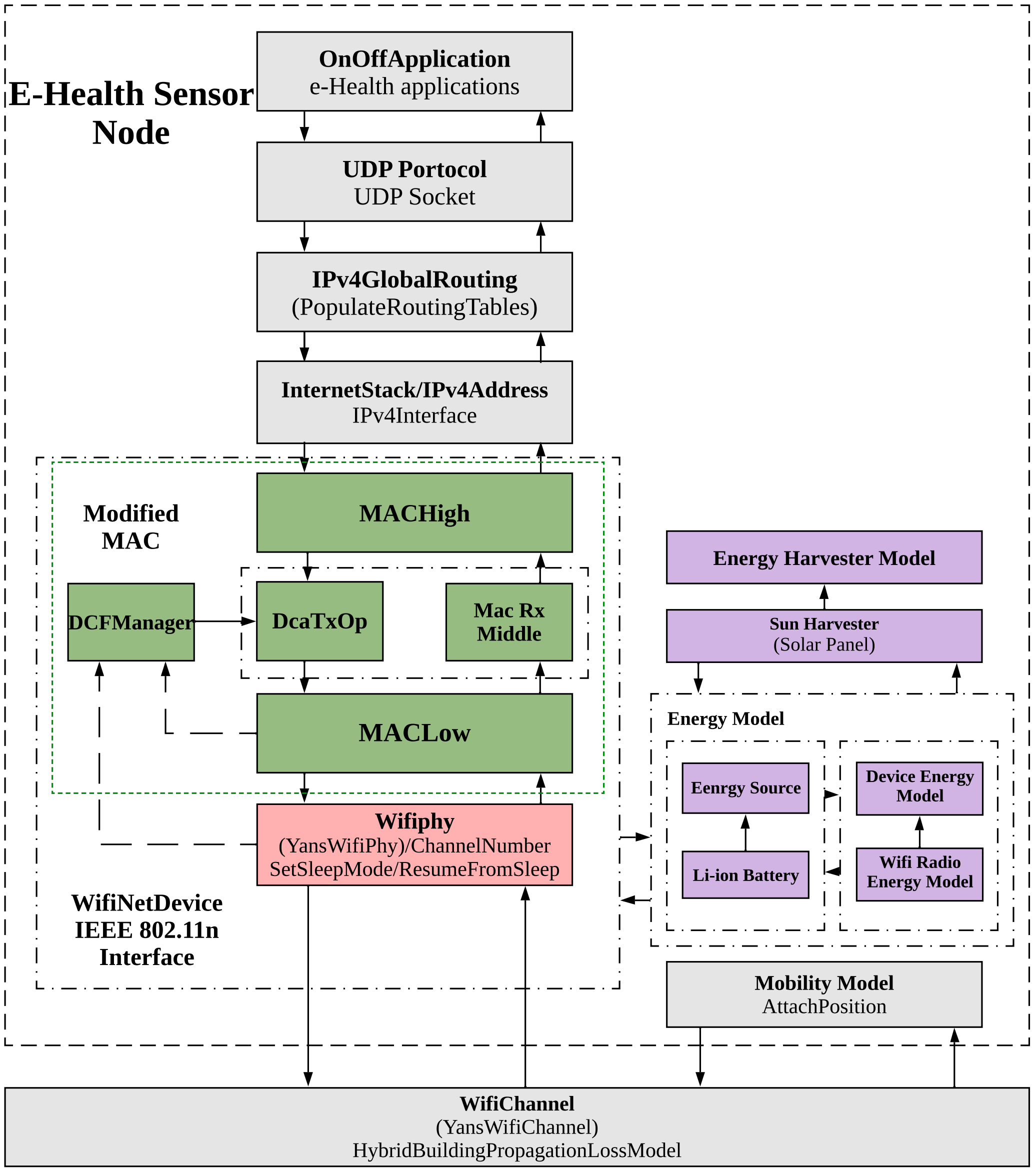


Figure 8. The layered structure of a sensor node (The modules in green, pink and purple represent the modified MAC layer, PHY layer, energy model, and energy harvester, respectively).

$$P_{\text{Sun Harvester}} = \eta_{\text{sc}} \times \eta_{\text{DC}-\text{DC}} \times D_{\text{Panel}} \times I_{\text{M}}(t) \tag{2}$$

where $P_{\text{Sun Harvester}}$ is the total harvested power, η_{sc} and $\eta_{\text{DC}-\text{DC}}$ represent the solar cell efficiency and DC to DC converter efficiency, respectively. $I_{\text{M}}(t)$ is the insolation parameter, which is perceived by the surface of solar panel and is obtained through Equation (3).

$$I_{\text{M}}(t) = I_{\text{direct}}(t) + I_{\text{diffused}}(t) \tag{3}$$

According to Equation (3), $I_{\text{direct}}(t)$ and $I_{\text{diffused}}(t)$ represent the direct radiation of the sun and diffused radiation of the sun, respectively. These parameters may vary during the year and depending on the position of the sun and the day time.

The general expression to obtain the energy consumption of wireless communication in IEEE 802.11 is defined through Equation (4) [61]:

$$E_{\text{Total}} = T_{\text{Rx}} \times P_{\text{Rx}} + T_{\text{Tx}} \times P_{\text{Tx}} + T_{\text{Sl}} \times P_{\text{Sl}} + T_{\text{Id}} \times P_{\text{Id}} \tag{4}$$

The power consumption of each state (reception, transmission, sleep, and idle) is the multiplication of the power consumption of that state to its corresponding duration.

4.4. Evaluation Metrics

Our system model is evaluated in terms of the following metrics.

4.4.1. End-to-End Delay

This metric represents the average of the mean delay parameter for all the network stations. The mean delay parameter is considered when the source generates the frame until it reaches its destination. Thus, it includes delays due to transmission, queuing, and contention [62].

4.4.2. Throughput

This metric refers to all the data frames that have been received successfully at the destination of the communication. This metric is obtained through Equation (5) [62].

$$S = \frac{\text{Rx}_{\text{Bytes}} \times 8}{\text{Tx}_{\text{Time}}} \tag{5}$$

where the Rx_{Bytes} is the number of the received frames in bytes, and Tx_{Time} is the duration between the last received frame and the first transmitted frame.

4.4.3. FER

This metric is calculated through Equation (6). Since in IEEE 802.11, all the successfully received frames by the destination are acknowledged, to obtain the Frame Success Rate (FSR), we divided the number of acknowledged frames by the total transmitted frames [63].

$$FER = 1 - FSR \tag{6}$$

4.4.4. Collision Rate

The collision occurs when two or more stations try to send data frames over the shared channel simultaneously. This metric is calculated through Equation (7).

$$Collision\ rate = \frac{\text{Rx}_{\text{error}}}{\text{Rx}_{\text{error}} + \frac{\text{RxOk}}{2}} \tag{7}$$

where Rx_{error} and Rx_{Ok} represent the total number of the frames that have been received unsuccessfully and successfully, respectively. Since in a successful transmission Rx_{Ok} is taken into account twice (one for the data frame and one for the ACK frame), to calculate the collision rate value, we need to divide Rx_{Ok} by 2.

4.4.5. PLR

This metric is calculated by Equation (8).

$$PLR = 1 - PDR \tag{8}$$

where the Packet Delivery Ratio (PRD) is the number of delivered packets divided by the total number of sent packets [62].

4.4.6. Fairness

This metric is defined through Jain's fairness index (see Equation (9)), which determines the share of each station in the network resources [64]. This value is bounded between 0 and 1 (all stations have the same share of resources).

$$Fairness = \frac{(\sum_{i=1}^{n} S_i)^2}{n \times \sum_{i=1}^{n} {S_i}^2} \tag{9}$$

where S_i is the throughput of the ith station, and n represents the number of the stations in the network.

4.4.7. Objective Function

$$OF = \frac{\text{Remaining energy}}{\text{Delay} \times PLR} \tag{10}$$

Since, in this paper, our target is to reduce energy consumption while maintaining the QoS requirement for medical applications, there is a need to define the level of QoS parameters for each medical application. For this reason, Table 4 is proposed based on the existing literature on real-time, emergency, and medical applications. Medical monitoring applications, along with video and telemetry alarm, are time-sensitive applications, while the Electronic Medical Record (EMR) is not a time-sensitive application. The ECG and Electroencephalogram (EEG) applications are considered applications with moderate latency, which means the end-to-end delay needs to be lower than 250 ms. In contrast, since a telemetry alarm is considered an emergency application, it requires a lower end-to-end delay (<100 ms). In EMR and video, this value can be higher(<400 ms). The required bandwidth for all medical applications remains the same (1 Mbps); however, in the case of video streaming, due to its high data rate, larger bandwidth is required. The PLR metric has to stay under 10% for all the medical applications and emergency services. However, in the case of video streaming, this value has to reduce to 5%. In Section 6, we will validate our analysis and obtain results based on Table 4.

Table 4. Quality of service requirements for e-Health applications.

Application Type	QoS Parameters				
	End-to-End Delay (ms)	**Required Bandwidth (Mbps)**	**Packet Loss Ratio (%)**	**Jitter (ms)**	**Sensitivity to Context**
ECG [40,65,66]	<250	1	<10	25	✓
EEG [40,65,66]	<250	1	<10	25	✓
EMR [40,67,68]	<300	1	<10	30	✗
Telemetry alarm [40,65]	<100	1	<10	25	✓
Video [69]	150–400	2	<5	30	✗

5. Simulation Setup

To evaluate the performance of the proposed system model, we implement a dense solar-based Wi-Fi network in a field hospital in the ns-3 simulation environment. In this section, we explain the simulation setup environment under designated conditions.

5.1. Network Scenario Definition and Assumptions

We consider a field hospital to be the simulation environment, where the relevant propagation loss model is the hybrid buildings propagation loss. The field hospital has one floor of 3 m height off the floor. The type of the hospital is considered an office-type building. The area of the field hospital is 40 m × 80 m, and the size of each room inside the field hospital is defined as 20 m × 20 m. The rooms are separated via wooden walls, and the external walls are considered concrete with windows. We locate one AP in the center of each room and associate the n number of non-AP stations to each AP. The stations are arranged in a circular pattern around the AP in each room, ranging in the distance from 1 to 10 m, and connect with the AP in the uplink direction. In this paper, the transmission performance is based on the IEEE 802.11n amendment. This represents a worst-case scenario since IEEE 802.11n uses the 2.4 GHz frequency band, which suffers from interference that impacts its performance, particularly in dense environments. In each set of simulations, to evaluate the performance of the network model, we consider the network size of five non-AP stations associated with each AP. The layout of the deployment when n = 5 is illustrated in Figure 9, where the brown lines represent the internal walls, and the black lines demonstrate the external walls. Moreover, the blue triangles and red circles represent APs and non-AP stations, respectively. In addition, the depicted numbers on the X and Y dimensions, represent the length of each room corresponding to these dimensions.

Each station is equipped with four different e-Health applications (ECG, EEG, EMR, and Telemetry alarm) in the simulations. The demonstration of the physical and default EDCA MAC layers parameters and medical traffic characteristics for the simulation are detailed in Table 5, Table 1 and Table 6, respectively.

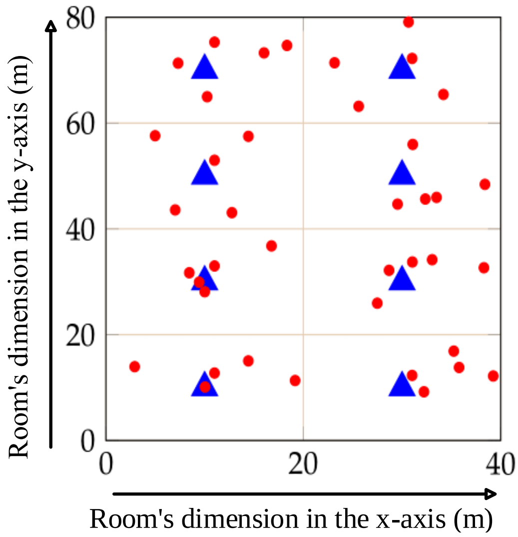


Figure 9. Layout of the Wi-Fi deployment in field hospital.

According to the priority of each e-Health application, specific access categories are defined for them. Telemetry alarm has the highest priority (AC_{VO}) among the selected applications in these network evaluations, and ECG, EEG, and EMR have the lowest priority (AC_{BE}). To calculate the ON-OFF period in the case of the telemetry alarm, since the traffic pattern shows 3.6 events per hour and each event duration is 1 s, we divide the number of events per hour to find the probability of the ON period (0.001) and the probability of the OFF period is 0.999. In the case of EEG [70] the probability of the OFF period is defined as 0.71; consequently, the ON probability is 0.29. In the case of EMR, since it represents the medical file transferring, it has a probability of 0.05 for the ON period and 0.95 OFF period. This means that file transmissions are not frequent. In the end, in the case of ECG, the probability of the ON period is defined as 0.65, and the probability of OFF duration is 0.35 [71]. Since ECG and EEG are both telemonitoring applications, the traffic type for ON and OFF is defined as the Constant Bit Rate (CBR). However, telemetry alarms and EMR have exponential traffic types (cf. Table 1).

Table 5. Physical layer parameters for simulation.

Parameter	Value
Wireless Standard	IEEE 802.11n
Frequency band	2.4 GHz
Physical transmission rate	MCS 5 for data frames
Propagation loss model	Hybrid building propagation loss
External Wall penetration loss	7 dB
Internal Wall penetration loss	4 dB
Transmission power	16 dBm
Energy detection threshold	−62 dBm
CCA mode1 threshold	−82 dBm
Guard interval	Short
Channel bandwidth	20 MHz
Channel Number	1
Aggregation	Disable
Stations per AP	5

Table 6. Traffic characteristics in the simulation study.

Traffic Type	**ECG**	**EEG**	**EMR**	**Telemetry Alarm**
Access Category	**BE**	**BE**	**BE**	**VO**
Traffic model	ON-OFF (0.650–0.350) CBR [72]	ON-OFF (0.29–0.71) CBR [40]	ON-OFF (0.05–0.95) Exponential [40]	ON-OFF (0.001–0.999) Exponential [40]
Data rate	12 kbps [71]	32 kbps [73]	4.1 Mbps [40]	5 kbps [40]
Packet size (Bytes)	147 [40]	155 [73]	1528 [40]	668 [74]

Moreover, each non-AP station is equipped with a solar panel with the dimension of 17 cm^2 whose size is matched with a remote blood oxygen monitoring [75]. Furthermore, the geographic coordination of the panel is set to the Barcelona city with a latitude of 41.3851°, longitude of 2.1734°, and altitude of 12 m above the sea. To obtain the energy consumption of each state of transmission, the current consumption of these states is defined according to to [76]. Additionally to the solar panel, each non-AP station is equipped with a Li-ion battery as a source of energy, whose characteristics are listed in Table 7.

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Table 7. Energy-related parameters.

Parameter	Value
Panel dimension [58]	17 cm^2
Panel latitude [58]	41.3851°
Panel longitude [58]	2.1734°
Panel altitude [58]	12.000 m
Harvesting update interval [58]	0.100 s
Initial energy [77]	100.000 J
Initial voltage [77]	3.200 v
Nominal voltage [77]	4.000 v
Exponential voltage [77]	4.000 v
Rated capacity [77]	0.950 Ah
Nominal capacity [77]	1.600 Ah
Exponential capacity [77]	0.200 Ah
Internal resistance [77]	0.035 Ω
Minimum threshold voltage [77]	3.000 v
Idle current [76]	0.233 A
Transmission current [76]	0.466 A
Reception current [76]	0.300 A
Sleep current [76]	0.020 A
CCA_Busy [76]	0.273 A

This setup permits us to examine the performance of our proposed algorithm by varying the CW value as a MAC parameter together with the offered sleep/wake-up method.

Next, the energy consumption based on the different communication states is analyzed.

5.2. Energy Consumption of Each Transmission State

To completely understand the total energy consumption in each transmission state of the communication, we analyze the network performance under saturated traffic (there is always a frame to transmit) and non-saturated traffic with and without applying the sleep/wake-up method.

According to Figure 10, which demonstrates the energy consumption of each state of transmission for the selected scenarios, in the case of saturated traffic (with/without sleep), the most consuming energy is the reception state. The reason behind it is that in Wi-Fi standard communications, the stations always sense the shared medium and receive the preamble frame of the communications of all the contenders. Then they decode the preamble frames only if they are meant for those stations. This procedure has a considerable impact on energy consumption under saturated conditions. In contrast to the saturated condition, in the case of the non-saturated network condition, since most of the time stations are in the idle state, almost 80% of the consumed energy belongs to this state (cf. Figure 10). In addition, Figure 10 coveys that applying sleep/wake-up mode reduces the energy consumption from 23.77 J to 14.14 J and from 27.55 J to 15.17 J in non-saturated and saturated scenarios, respectively. In the case of the saturated scenario, although the energy consumption of all the transmission states reduces, this parameter is reduced to more than half for the reception state. In the case of the non-saturated scenario, the most consuming energy state is the idle state, whose energy consumption reduce to half by applying the sleep/wake-up method.

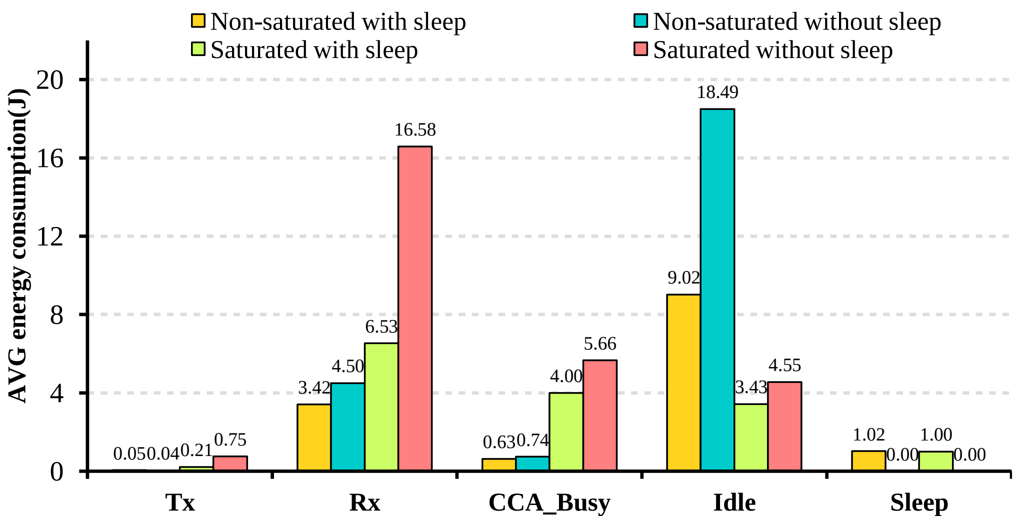


Figure 10. The idle and Rx states are responsible for most of a node energy consumption.

6. Performance Evaluation and Discussion

In this section, through extensive simulations, we assess the performance of our AP coordination-based optimization algorithm in a solar-based dense Wi-Fi network implemented in a field hospital. As described in Section 4, to find the most proper CW combination for each medical application, the proposed simulations run in the selected environment for each application individually based on three steps (i) CW changes on all cells of the network, (ii) CW changes only on slave cells, (iii) CW changes only on master cells. Then, we apply the sleep/wake-up mode to improve the network performance regarding energy consumption. The analysis is based on the PLR and end-to-end delay as the medical-grade QoS feature, FER, and energy consumption. Finally, we demonstrate the importance of the energy harvester implementation in the network.

6.1. Adaptation to the CW Changes on All the Cells

Although IEEE 802.11 standard defines specific CW values for each AC, these values may need to vary based on the network conditions for each type of traffic. The selection of proper CW values has an essential impact on the network's performance. For instance, the network will suffer from a long delay if the CW values are selected as very large values. In contrast, in the case of selecting a very small value for CW, the collision rate will increase. Since we consider three different medical applications with distinct traffic models, we must first find the most proper CW combination for each application in these simulations.

For this reason, we first increase the CW combinations from default values (the standard combination for AC_{BE}) to cases 1, 2, 3, and 4 in all the cells. Although different possible combinations can be defined, to summarize the results, we consider four cases in our simulations that are listed in Table 8. In these simulations, five non-AP stations are associated with each AP during 30 s of the simulation run. We repeat the exact simulation 10 runs to obtain more accurate results.

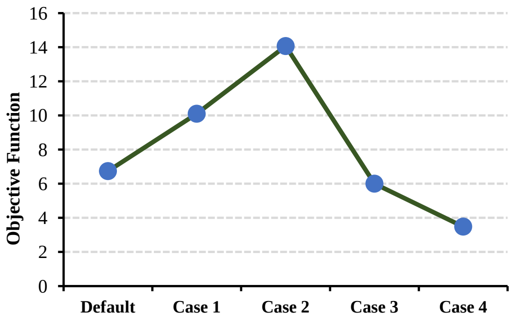
Table 8. Label adaptation of CW combinations to find the optimal point.

Combination of CW_{min} and CW_{max}	Adapted Label in the Case of CW Changes in All the Cells
31–1023	Default
63–1055	case 1
127–1119	case 2
255–1247	case 3
511–1503	case 4

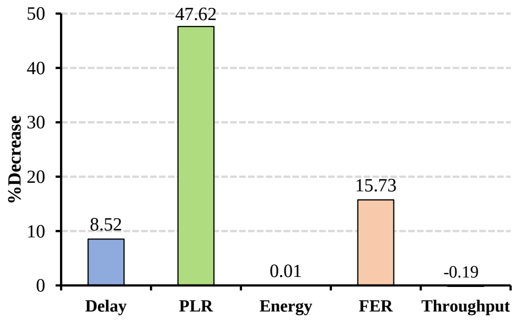
6.1.1. CW Changes under ECG Application

Figure 11a shows the objective function in the case of ECG application when CW changes in all the cells. According to the objective function, the most improvements in the network belong to case 2. We can see that the objective function decrease in cases 3 and 4 due to the large CW combinations, which delay the transmission. The PLR parameter can benefit from increasing the CW combination. However, selecting a large CW combination, such as the ones in cases 3 and 4, increases the packet loss, which causes a reduction in the objective function. The reason for this is that all the non-AP stations are delayed for a longer duration.

In contrast to the delay and PLR parameters, energy consumption and FER can benefit from increasing the CW combination, where FER has a significant reduction (47.62%) among all other metrics (cf. Figure 11b). Although the energy consumption is decreased, this reduction is almost 0.01% and is negligible. The reason for this is that selecting a larger CW value reduces the collision ratio and FER, which both impact energy consumption. Nevertheless, to choose the most proper combination and consider all four metrics together, and based on the objective function, case 4 has the worst impact on the network performance, and case 2 has the most suitable case for ECG application. In addition to the QoS metrics, the results indicate a possible but slight improvement in throughput parameters.



(**a**) Objective Function



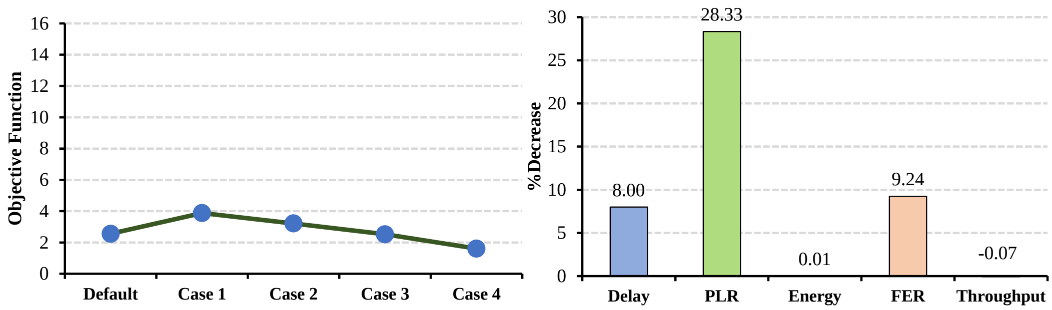
(**b**) Performance at the optimal point

Figure 11. ECG QoS metrics and energy consumption under CW changes for all cells.

6.1.2. CW Changes under EEG and EMR Applications

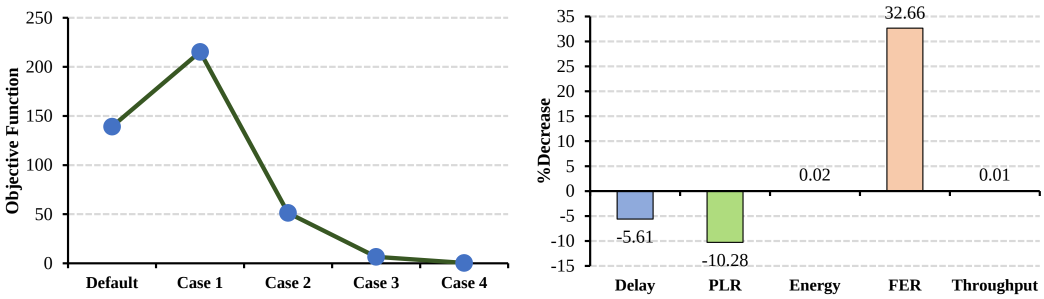
According to the objective functions for EEG and EMR applications, which are illustrated in Figures 12a and 13a, the optimal case in both applications is case 1. Moreover, the objective functions indicate that case 5 has the worst impact on the network performance. The reason for this is that in case 5, the network suffers from large delay and PLR.

As shown in Figure 12b, all the metrics in the optimal case are improved even though there is a slight increase in the throughput parameter. However, in the case of EMR application (cf. Figure 13b), although FER is decreased by 32.66%, which causes a slight reduction in the energy consumption, PLR and delay are increased by 10.28% and 5.61%. Nevertheless, since the increasing percentage in PLR and delay are drastic, these two metrics stay below the QoS restrictions for EMR application. By comparing the FER in Figures 12b and 13b, we convey that a longer delay causes more reduction in FER and energy consumption. Therefore, in case 4, with a larger CW combination, there is a huge improvement in network performance in terms of FER and energy consumption. However, we cannot consider this case to be the optimal point due to its large PLR and delay that cause a drastic reduction in the objective function. Thus, we need to take into consideration the best value of all the metrics simultaneously. For this reason, case 2, with the least PLR and delay for both applications, has the best network performance under this CW combination. As objective functions demonstrate, this case is considered to be the optimal CW combination.



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 12. EEG QoS metrics and energy consumption under CW changes for all cells.



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 13. EMR QoS metrics and energy consumption under CW changes for all cells.

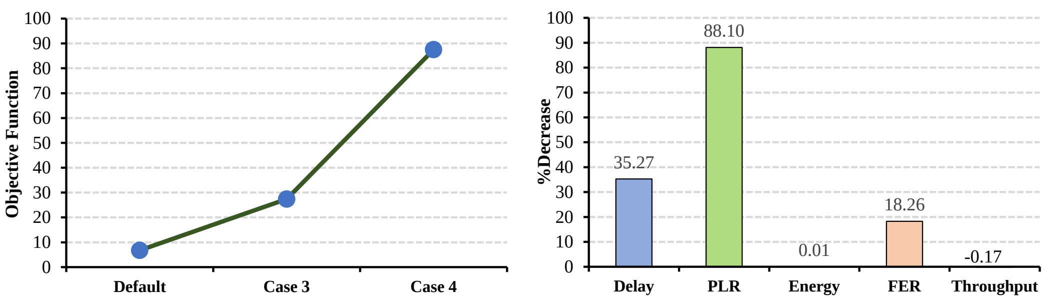
We observe that the proper CW combination for ECG application is larger than the CW combination for EEG and EMR applications. The reason for that is the traffic type of this application with a larger probability for the ON period compared to EEG and EMR applications.

6.2. Adaptation to CW Changes on Slave Cells

In the next step, we evaluate the network's performance when the master cells keep their CW values constant based on the previous step (optimal combination) and request the slave cells to increase their CW values.

6.2.1. CW Changes under ECG Application

Increasing the CW values on the slave cells allows the master cells to improve their medical-grade QoS metrics and energy consumption performance by starting the transmission faster than the slave cells. The larger the CW combination selected, the more the network benefits. As shown in Figure 14a, by comparing the obtained results to the default case, the maximum objective function belongs to case 4. However, similar to the previous results, the percentage reduction in energy consumption is negligible.

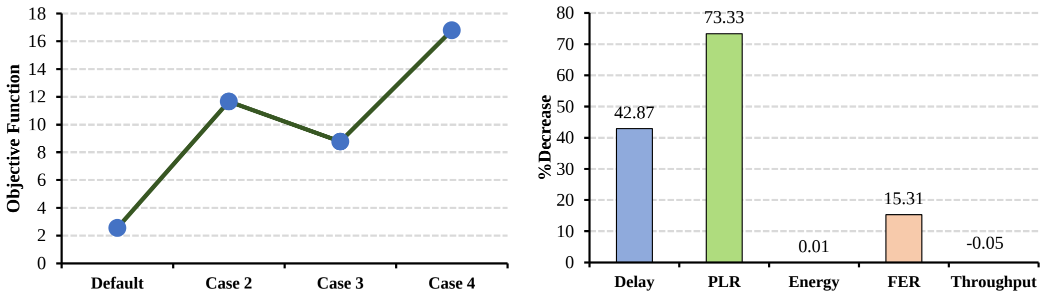


(**a**) Objective Function (**b**) Performance at the optimal point

Figure 14. ECG QoS metrics and energy consumption under CW changes for slave cells.

6.2.2. CW Changes under EEG and EMR Applications

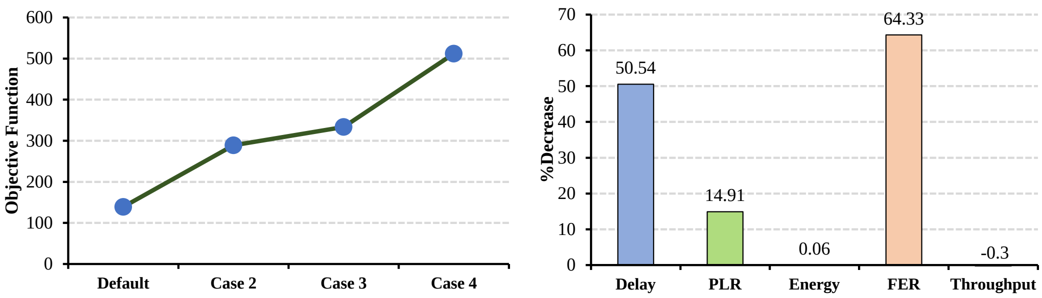
Similar to the ECG application, in the case of EEG and EMR applications, all the QoS metrics benefit from a larger CW selection. Increasing the CW values for EEG application has the most impact on the PLR parameter by decreasing 73.33% from the standard value (cf. Figure 15b), and the EMR application has the most impact on the FER by a 64.32% decrease (cf. Figure 16b).



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 15. EEG QoS metrics and energy consumption under CW changes for slave cells.

We observe that to increase the performance of the master cells and give more opportunity for them to transmit faster with less collision, the CW values in the slave cells need to be larger than the CW values in the master cells. However, selecting a minimal CW value for the master cell increases the collision among them and degrades their performance. For this reason, we need to find the most proper CW combination for master cells as well.



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 16. EMR QoS metrics and energy consumption under CW changes for slave cells.

6.3. Adaptation to CW Changes on Master Cells

As mentioned previously, by increasing the CW value on slave cells and delaying their transmissions, the master cells will have more opportunities to start transmission. Additionally, shrinking the CW values on master cells will offer them even more opportunities to start the transmissions faster. However, this can increase the collision rate among master cells with smaller CW values. Therefore, there is an optimal CW value for master cells to increase their transmission opportunity. In this step, the slave cells keep the CW values constant based on the previous step to case 4 for all three applications and gradually shrink the CW values on the master cells according to Table 9.

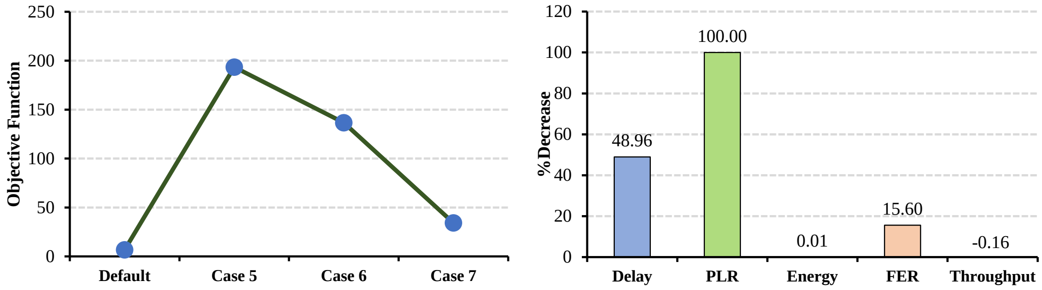
Table 9. Label adaptation of CW combinations in master cells.

Combination of CW_{min} and CW_{max}	Adapted Label in the Case of CW Changes in Master Cells
31–1023	Default
123–1116	case 5
119–1112	case 6
115–1108	case 7

6.3.1. CW Changes under ECG and EEG Applications

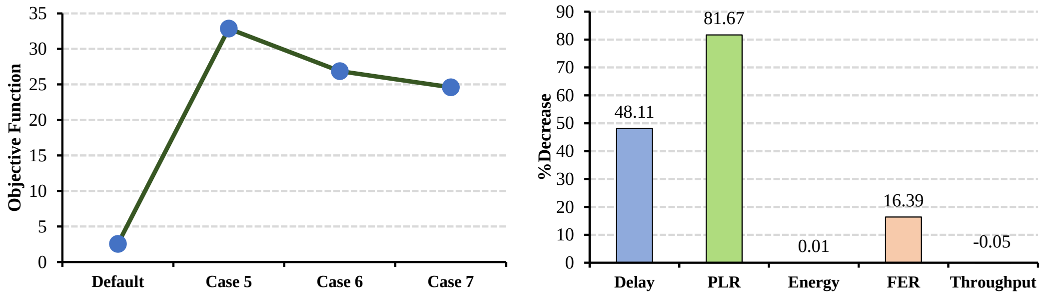
In this set of simulations, the CW values in master cells shrink from case 5 to case 7. In the ECG application, as shown in Figure 17a, case 5 is the optimal selection, where the PLR benefits more than other metrics and decreases by 100% (cf. Figure 17b). However, this reduction cannot be observed in energy consumption, where the decrease percentage is only 0.01%. Similarly, in the EEG application, as the objective function demonstrates, case 5 is the optimal CW combination, where the delay and FER benefit more than other metrics (cf. Figure 18b).

In this combination, CW values in slave cells stay large enough to allow master cells to start communication before them. The CW values in master cells are small enough to make their transmission faster while maintaining the level of medical-grade QoS requirements below the restrictions.



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 17. ECG QoS metrics and energy consumption under CW changes for master cells.

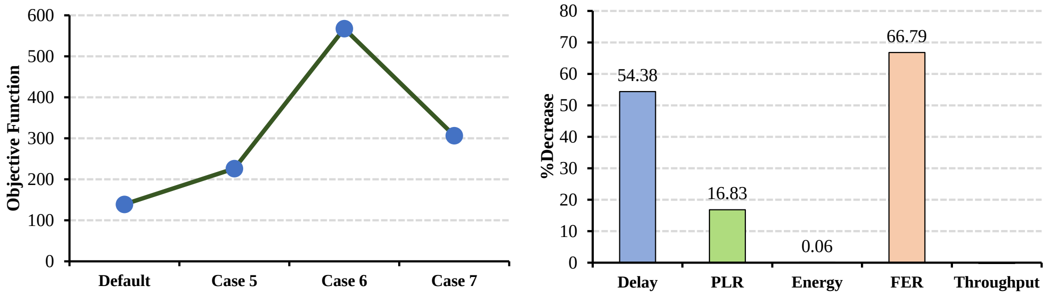


(**a**) Objective Function (**b**) Performance at the optimal point

Figure 18. EEG QoS metrics and energy consumption under CW changes for master cells.

6.3.2. CW Changes under EMR Application

In contrast to the ECG and EEG applications, in EMR application case 6 demonstrates the maximum decrease in delay and PLR (cf. Figure 19b and while having an acceptable level of decrements in FER 66.79%.



(**a**) Objective Function (**b**) Performance at the optimal point

Figure 19. EMR QoS metrics and energy consumption under CW changes for master cells.

The analysis based on the obtained results indicates that, although the medical-grade QoS requirement is met through our AP coordination-based algorithm, the energy consumption reduction compared to the standard CW combination is not as much as QoS metrics. For this reason, in the following subsection, we will introduce the sleep/wake-up mode to reduce the network's energy consumption with a focus on master cells.

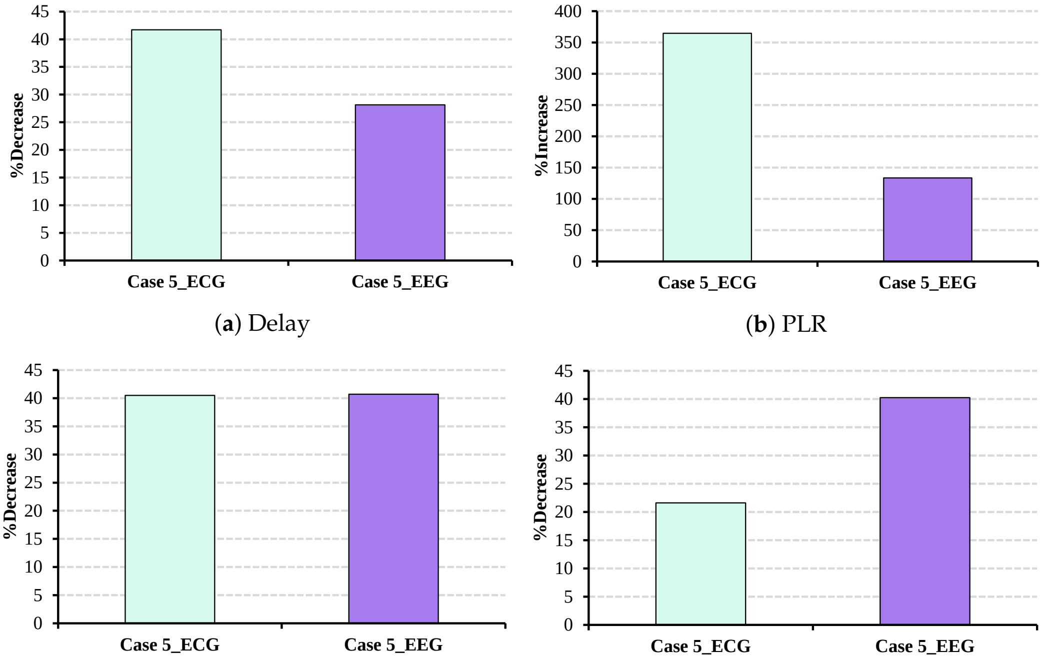
6.4. Sleep/Wake-Up Mode with CW Changes

As we explained in Section 4, to reduce the network's total energy consumption, we introduce a sleep/wake-up mode to the network with the optimal CW combinations in both master and slave cells. According to this method, for the case of simplicity, the wake-up duration and sleep duration for the master cell are defined as 0 s–0.5 s and 0.5 s–1.0 s, respectively. In this method, while the master cell is in sleep mode, the slave cell has permission to transmit, and during the wake-up duration of the master cell, it is sent to sleep mode. To avoid losing frames and degrading the network's performance in terms of throughput for each medical application, we double the data rate. In this case, in the ON period (0.5 s), each application transmits the same amount of data sent before.

Compared to the obtained results of the standard without sleep/wake-up mode, although PLR in both ECG and EEG applications increases, it still stays below the QoS restrictions. Nevertheless, other QoS parameters such as delay and FER improve, and energy consumption experiences a considerable reduction of almost 40% in both applications (cf. Figure 20c).

6.5. Impact of Energy Harvester

As we explained throughout the paper, IoT systems benefit from deploying energy harvesting technologies, specifically when providing a reliable energy source for devices. Thus, to reveal the critical role of the energy harvester in our simulations, we compared the network's remaining energy in two scenarios while changing the size of the solar panel. On the one hand, with the implementation of the proposed algorithm, and on the other hand, without the proposed algorithm. The results indicate that in the network without the algorithm's implementation, larger panel size is required to provide enough energy to the network system (the smallest possible dimension, in this case, is 47 cm^2). However, when applying the algorithm, it is possible to reduce the size of the panel from 47 cm^2 to 7 cm^2, which means the harvested energy from a panel size of 7 cm^2 will be sufficient to keep the system to powered up. This comparison, which is illustrated in Figure 21, conveys the effectiveness of the proposed algorithm on the solar panel size reduction, and consequently, the feasibility of the cooperation of the energy harvesting technologies and Wi-Fi-based IoT systems.



(**a**) Delay (**b**) PLR

(**c**) Energy consumption (**d**) FER

Figure 20. Desired QoS metrics and energy consumption under CW changes with sleep/wake-up mode.

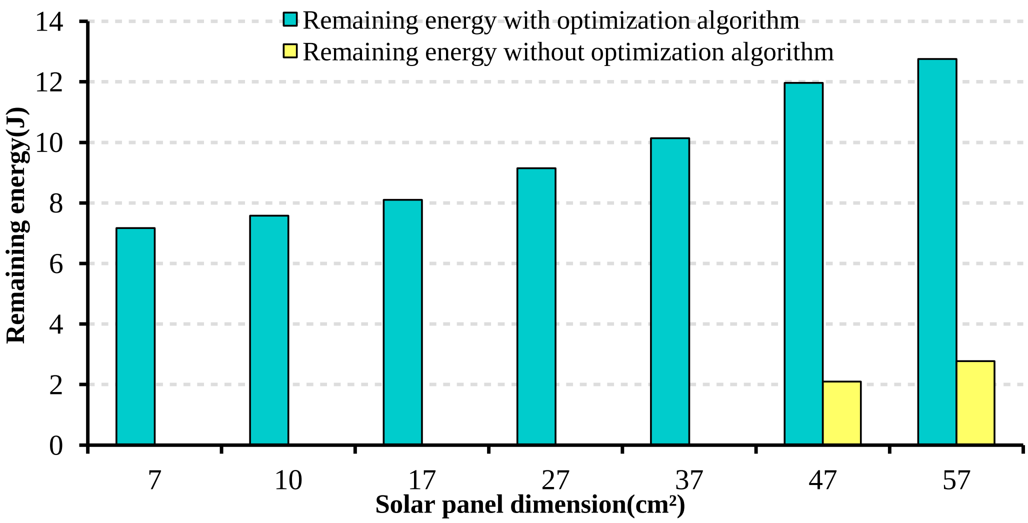


Figure 21. Impact of the proposed algorithm on the selection of the solar panel.

6.6. Discussion

Results show that the EDCA CW selection should be adapted for different medical applications. For instance, in the presented work, since the traffic characteristics of the considered medical applications (ECG, EEG, and EMR) are varying, there is not a unique valid CW combination. Thus, there is an optimal CW combination within the same AC for each application. Furthermore, according to the results, the network performance in terms of medical-grade QoS, in this case, delay and PLR, can be improved by introducing AP coordination within IEEE 802.11 standard. In this context, first, the transmission in slave cells is delayed by increasing their CW values, then the CW values shrink in master cells to give them more opportunity to start the transmission. However, there is an optimal value for CW values in both master and slave cells to not increase the collision rate probability by decreasing the CW and delay the slave a lot by increasing this value. Additionally, the proposed sleep/wake-up mode considerably reduces energy consumption in medical applications without violating the QoS restrictions. Finally, we indicate the importance of the energy harvester in the system and the effectiveness of our proposed algorithm, which can reduce the dimension of the required solar panel.

7. Conclusions and Future Works

This paper presents a novel e-Health-oriented communications system, simulated in ns-3, where the cooperation of energy harvesting technologies with Wi-Fi-based IoT systems is possible. We introduced an AP coordination-based optimization algorithm in the MAC layer that encounters the optimal CW combination in both master and slave cells separately to improve the non-AP station's performance associated with the master APs in terms of medical-grade QoS. The results indicate that the proposed algorithm can improve the level of the QoS metrics for considered applications at most 80% (different for various applications and metrics). In addition, the proposed algorithm aligned with the sleep/wake-up method introduces a reduction of more than 40% in the network's energy consumption while maintaining the QoS metrics below the restriction level. We consider that this paper could shed light on enabling the integration of energy harvesting in IoT systems. In future work, this study can be expanded in terms of adapting the proposed algorithm to other MAC layer parameters rather than just CW. In addition, to covey a more profound analysis, the per non-AP station evaluation for a more dense network can be conducted.

Author Contributions: G.F.: Conceptualization, Methodology, Software, Validation, Investigation, Writing-Original draft preparation. M.S.A.: Methodology, Software, Validation, Investigation, Writing-Review and editing, Visualization, Supervision. J.M.-S.: Methodology, Validation, Writing-Review and editing, Supervision, Project administration. All authors have read and agreed to the published version of the manuscript.

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5

Introducing reinforcement learning in the Wi-Fi MAC layer to support sustainable communications in e-Health scenarios

This chapter introduces innovative contributions, including an RL-based optimization algorithm for solar-powered Wi-Fi networks, which was published as a journal article in *IEEE Access*. The algorithm is specifically designed to integrate EH technologies and ensure QoS for medical applications. The algorithms effectively reduce energy consumption and meet QoS parameters for medical applications, such as PLR and E2E delay, thereby improving network performance in medical-grade scenarios. This innovative approach highlights the novelty of the research and its potential to advance the field.

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RESEARCH ARTICLE

Introducing Reinforcement Learning in the Wi-Fi MAC Layer to Support Sustainable Communications in e-Health Scenarios

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ABSTRACT The crisis of energy supplies has led to the need for sustainability in technology, especially in the Internet of Things (IoT) paradigm. One solution is the integration of passive technologies like Energy Harvesting (EH) into IoT systems, which reduces the amount of battery replacement. However, integrating EH technologies within IoT systems is challenging, and it requires adaptations at different layers of the IoT protocol stack, especially at the Medium Access Control (MAC) layer due to its energy-hungry features. Since Wi-Fi is a widely used wireless technology in IoT systems, in this paper, we perform an extensive set of simulations in a dense solar-based energy-harvesting Wi-Fi network in an e-Health environment. We introduce optimization algorithms, which benefit from the Reinforcement Learning (RL) methods to efficiently adjust to the complexity and dynamic behaviour of the network. We assume the concept of Access Point (AP) coordination to demonstrate the feasibility of the upcoming Wi-Fi amendment IEEE 802.11bn (Wi-Fi 8). This paper shows that the proposed algorithms reduce the network's energy consumption by up to 25% compared to legacy Wi-Fi while maintaining the required Quality of Service (QoS) for e-Health applications. Moreover, by considering the specific adjustment of MAC layer parameters, up to 37% of the energy of the network can be conserved, which illustrates the viability of reducing the dimensions of solar cells, while concurrently augmenting the flexibility of this EH technique for deployment within the IoT devices. We anticipate this research will shed light on new possibilities for IoT energy harvesting integration, particularly in contexts with restricted QoS environments such as passive sensing and e-Healthcare.

INDEX TERMS Medical Internet of Things, access point coordination, sleep/wake-up, machine learning, reinforcement learning, energy harvesting technologies, passive communications.

I. INTRODUCTION

According to Cisco, approximately 30 billion connected Internet of Things (IoT) devices will exist by the end of 2023 [1], this fast development and deployment of IoT ecosystems, from smart cities to smart agriculture, have a negative impact on the environment and planetary resources [2]. One crucial factor in mitigating these harmful effects is sustainability, which can be conducted through various passive technologies such as Energy Harvesting (EH) techniques. EH technologies are environment-friendly and reliable approaches that have the ability to expand the lifespan of IoT devices, enable multifunctional wireless networks, while also diminishing the disadvantages of conventional batteries. The wind and solar photovoltaic capacity experiences a threefold growth, surging from approximately 75 GW in

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2020 to 230 GW by 2030 [3]. In addition, EH technologies are the leading part of the Net Zero 2050 project [4],[1] in which the trade-off between emitted greenhouse gases to the atmosphere and the amount of removed greenhouse gases from the atmosphere is balanced. On the one hand, Medical IoT (MIoT) allocates 20% of the global IoT systems [5], and on the other hand, healthcare is responsible for 4-5% of the emissions of greenhouse gases. Thus, using these technologies in MIoT delivers a threefold advantage: reducing the amount of greenhouse gas emissions [6], lowering maintenance costs, and improving human well-being [7].

An illustrative example of the importance of the EH in MIoT can be presented in a pandemic situation, such as the COVID-19 crisis in 2020. Hospitals' total capacity was nearly occupied by patients needing special medical care, and thus, field hospitals or mobile medical units had to be quickly assembled under critical circumstances. Since one essential issue in establishing mobile medical units is to provide reliable and adequate energy sources, cooperating energy harvesting technologies (solar cells, piezoelectric, and thermoelectric harvesters) might assist in offering sustainable communications and energy sources, especially for medical devices and monitoring systems.

Pursuing sustainability in Information and Communication Technology (ICT), specifically wireless communications, is a concerning issue where carbon-based energy carriers fuel systems. It has been estimated that around 80% of greenhouse gas emission is due to carbon-based energy carriers (fossil fuels such as coal, oil, natural gas, gasoline, and diesel fuel) [8]. As stated by the authors in [9], wireless communication constitutes 75% of ICT, with wireless being the predominant mode of communication in IoT systems. Wireless communications presently contribute to 4% of the total global CO_2 emissions, which is projected to rise due to the growing number of connected devices. To reduce the emission of greenhouse gases, it is necessary to understand the energy requirement of the systems and minimize the usage of these energy carriers, whether by introducing EH technologies and renewable energy carriers or applying energy-efficient methods. In this regard, selecting an appropriate wireless technology and integrating it with a proper EH technique in terms of power density and form factor is essential for successful integration. Optimization algorithms such as channel adaptation or energy-aware routing algorithms have been used to reduce energy consumption at different layers of the IoT protocol stack. However, since Medium Access Control (MAC) layer operations consume most of the wireless communication's energy budget, this layer can benefit more from optimization algorithms such as channel access optimization methods. Given that advanced energy optimization methods involve the consideration of increasingly complex features, the significance of Machine Learning (ML) algorithms in this context cannot be underestimated.

[1]The the United Nations (UN) and the Intergovernmental Panel on Climate Change (IPCC) lead in promoting net zero emissions. The 2015 Paris Agreement, under the UNFCCC, urges nations to achieve net zero emissions by the latter half of the 21st century.

IEEE 802.11, commonly referred to as Wi-Fi, is the dominant wireless communication technology in indoor IoT systems (it is reported that 51% of the wireless communication in 2022 belongs to Wi-Fi communication [10]). The channel access method of legacy IEEE 802.11 includes the contention-based Enhanced Distributed Channel Access (EDCA) mechanism, which defines four Access Categories (AC) for provisioning Quality of Service (QoS) for different traffic types based on the MAC layer parameters. The aforementioned EDCA mechanism is used to support service differentiation by assigning different Contention Window (CW) sizes, transmit opportunity (TXOP), Arbitration Inter-Frame Space (AIFS), and retransmission limit value. However, it faces inherent issues of using static parameters assignment of CW size AIFSN, TXOP limit, and retransmission limit without taking into consideration the current status of ACs as well as the number of stations competing to gain access to the shared channel. In addition, there might be another issue, where stations can act selfishly and choose a very small CW in order to increase their channel access [11]. This results in a decrease in channel access opportunities for well-behaved stations. Lastly, EDCA does not differentiate between applications with the same traffic type but different levels of QoS requirements. This means that applications with high QoS requirements may experience higher latency or packet loss than applications with low QoS requirements. Consequently, these issues affect the manner in which the stations contend to access the shared channel, which leads to more collisions and thus impacts the overall performance of the network. These issues become a complex problem in dense deployments, which are characterized by frequent collisions [12]. The increased collision rate can impact energy consumption as they need retransmissions and activating collision avoidance mechanisms, leading to increased energy usage. Therefore, integrating EH techniques with a dense Wi-Fi network in a medical environment poses significant challenges due to collisions and increased energy consumption, making it a complex problem. Moreover, the existing IEEE 802.11 channel access mechanism with predefined MAC layer parameter configurations is unable to meet the specific QoS requirements mandated in medical settings. Despite these obstacles, exploring the implementation of EH techniques in such networks remains essential to unlock their potential benefits.

In recent years, ML algorithms have demonstrated a powerful capability to improve and evolve optimization problems from classical optimization methods in wireless networks [13]. For instance, features such as the Access Point (AP) coordination mechanism in Wi-Fi 7 and beyond can reduce the network's energy consumption by coordinating the schedules of the transmission time between APs, and reducing the overall delay of the network [14]. To meet this feature, complex configurations, and non-linear optimization are required that can be fulfilled through ML-based algorithms. Thus, ML algorithms are necessary, particularly in the MAC layer operations and mechanisms, to make the configuration dynamic, flexible, and energy-efficient for dense and heterogeneous networks while provisioning QoS requirements. Furthermore, these algorithms can play a crucial role in optimizing the MAC layer to support EH techniques. By leveraging ML, the MAC layer can adaptively adjust parameters based on real-time network conditions and harvested energy availability. This integration of ML and EH enables intelligent resource management, reducing collisions, improving energy efficiency, and maximizing the benefits of energy harvesting in wireless networks. Through efficient resource allocation and intelligent energy management, ML-enhanced MAC layer operations help in enabling a more sustainable approach to wireless communication by minimizing energy waste and prolonging the lifespan of battery-powered devices.

To the best of our knowledge, this is one of the first papers that tries to achieve sustainability in IoT-based QoS-restricted[2] dense MIoT scenarios. Three ML-based algorithms are proposed which intend to guarantee the QoS requirements - End-to-End delay (E2E delay) and Packet Loss Ratio (PLR) - while maximizing the total remaining energy of the network and consequently reducing the emission of the greenhouse gases. This article is recapitulated in the following contributions:

- We propose novel RL-based optimization algorithms for a solar-based Wi-Fi system in a medical IoT scenario.
- We assume the AP coordination concept from the upcoming Wi-Fi amendment (IEEE 802.11bn) while supporting backward compatibility with the IEEE 802.11 standard.
- We present an objective function to maximize remaining energy and minimize E2E delay and PLR for medical-grade QoS criteria.
- We accomplish an extensive set of simulations on Network Simulator 3 (ns-3) to evaluate the suitability of our proposals.

The remainder of this article is structured as follows. In Section II, we highlight the relevant studies in the literature. The existing problem is elaborated in Section III. Sections IV and V explain the methodology and simulations setup, respectively. Section VI is devoted to the performance evaluation of the proposals' analytical discussions. Finally, in Section VII, we provide final remarks and future work.

II. RELATED WORK

Modifying and optimizing the MAC layer operations of IEEE 802.11 has undergone a lot of investigations and research studies. However, these optimization studies do not address the dense EH-based QoS-restricted environments, which require dynamic changes, such as medical IoT systems where real-time, emergency, and multimedia applications are employed.

A set of techniques described in the literature consists of modifying the initialization of the MAC layer parameters, such as CW, AIFS, and TXOP, to adjust the channel access scheduling in the EDCA mechanism. Dynamic initialization of AIFS is presented in [15] to support QoS requirements for real-time and non-real-time medical applications. Nevertheless, this algorithm is not able to meet QoS in a saturated condition. Other works intend to address QoS-restricted environments by defining fixed or dynamic CW values adaptation algorithms. In [16], the authors explain an algorithm that doubles the CW values when the channel is busy, or collision occurs, whereas in [17], the authors define a dynamic selection of CW values based on the traffic load of the network to reduce the collision rate and transmission delay in the network. However, these optimization algorithms modify the fundamental of the EDCA mechanism, and they may not be compatible with the IEEE 802.11 standardization. In one of the most recent MAC layer modifications [18], the authors proposed an enhanced Preliminary Channel Access (PCA) method, which allows the transmission for Real-Time Application (RTA) access to the channel faster than other transmissions compared to PCA and EDCA mechanisms. The aim of this study aligns with Wi-Fi 7, where low delay and high reliability are the two requirements for the RTA use cases. The proposed mechanism provides backward compatibility in Wi-Fi scenarios. However, this work does not include any energy-related analysis.

There are a few energy-harvesting MAC layer protocols in the literature which consider the integration of the energy harvesting technologies with WLAN communication. Some of these works try to achieve an energy-efficient MAC protocol even by only increasing the energy budget of the network or reaching an optimal energy consumption point. In [19], the authors propose algorithms to reduce the energy consumption of a Wi-Fi solar-based network. Whereas in [20], an optional energy-saving mode feature in IEEE802.11ah is evaluated along with the EH technique deployment. However, the authors do not consider QoS restricted environment in these works.

Another set of techniques used in the literature is based on ML. Specifically, RL is able to provide reliable solutions to complex decision-making problems. Recently, these techniques have attracted more attention among researchers in the wireless communication networks area. Proposing new features in the IEEE 802.11be and beyond to meet the IoT systems requirements (distributed management and deployment) may increase the Wi-Fi network's density, dynamic condition, and complexity. Thus, deploying RL-based algorithms becomes more influential in this scenario [21]. The RL-based algorithms can be deployed in IEEE 802.11 standard to optimize the existing techniques and the defined parameters, which lead to reducing the

[2]QoS-restricted scenario refers to a situation where the available network resources, such as bandwidth, capacity, energy, and processing power, are limited due to the high number of connected stations. This limitation creates challenges in delivering the desired level of service to all applications or users simultaneously.

collision probability, increased throughput, and optimized frame length [22], [23], [24]. Recent studies demonstrate that Deep RL (DRL) algorithm can improve the handovers in mmWave communications [25], optimize the resource unit allocation for multi-user scenarios [26], configure the channel bonding [27], or address the channel allocation and AP clustering issues in MIMO networks [28]. Other studies on RL-based algorithms focus on Wi-Fi management, such as the works presented in [29], [30] for channel and band selection or management architecture [31].

An RL-based optimization algorithm for updating the CW value based on the collision probabilities is proposed in [32], in which the throughput increases while the delay maintains a certain level. Although this mechanism introduces an optimal point between the collision rate probability and CW increase or decrease, it does not consider the network's total energy consumption and provision of QoS for applications with different traffic types.

As indicated in Table 1, most of the aforementioned studies benefit from the integration of the traditional RL with deep neural networks, such as Deep RL (DRL) to handle complex tasks, Deep Q-Network (DQN) to approximate the Q-value function, Deep Deterministic Policy Gradient (DDPG) to approximate both the policy and Q-value functions and offering better performance in continuous action domains, and Deep Q-Learning (DQL) to handle high-dimensional state spaces more effectively. In addition, some other approaches focus on maximizing the reward, such as Multi-Armed Bandit (MAB) or the ones that consider interaction between agents, such as Multi-Agent RL (MARL).

As stated in the introduction, while EH integration can help IoT systems attain sustainability by lowering the demand for traditional batteries, it also introduces new obstacles regarding physical dimensions, communication protocols, and user privacy. Thus, it is necessary to reduce the energy budget of the IoT system to tackle energy-related issues, which can be addressed through energy model optimizations. One energy model optimization, proposed in [33], was the first work to present the MAC layer operation modifications (optimal selection of CW initialization) based on the type of medical applications and AP coordination concept. However, the authors conclude that an ML algorithm would benefit the performance of such systems.

Table 1 demonstrates how our research contributes to the field by comparing the features of the current study with the relevant existing literature. According to the extensive study on the existing literature, we believe that several outstanding throughput and fairness optimization studies propose innovative solutions that need a comprehensive transformation and re-imagining of the IEEE 802.11 standard. Nevertheless, ensuring backward compatibility poses a complex challenge, as existing and old equipment cannot be changed. It is essential to highlight that our effort is to strongly achieve backward compatibility in the proposed RL-based algorithms that focus on optimizing the energy (remaining) of the network.

To the best of our knowledge, no RL-based MAC layer optimization assesses the feasibility of integrating energy harvesting technologies aligned with provisioning QoS for medical applications. Thus, this article enhances the previous work and improves the algorithm's flexibility to the dynamic behavior of dense networks by introducing RL-based optimization algorithms. These algorithms are able to reduce the energy consumption of the MAC layer operations in a solar-based Wi-Fi network while meeting specific QoS medical-grade parameters for medical applications like PLR and delay. Thus, this novel integration provides a fresh perspective and yields significant advancements in sustainable IoT-based Wi-Fi communication.

III. PROBLEM STATEMENT

The IEEE 802.11 MAC layer is a contention-based distributed layer that consumes most of the energy budget of the network due to associated collisions, retransmissions, and back-off mechanisms [34]. Figure 1 demonstrates the default access technique known as the two-way handshaking scheme [35].

To assess channel conditions prior to transmission, the traditional IEEE 802.11 protocol employs a technique known as Physical Clear Channel Assessment (PHYCCA) at each network node. By measuring the energy level in the channel, the node can determine whether it is above a predetermined threshold, called the carrier sensing threshold (CST). If the measured energy level exceeds the CST, indicating that the channel is occupied, the node will defer its transmission and wait for the channel to become available. This mechanism allows nodes to avoid transmitting when the channel is already in use, reducing the likelihood of collisions and improving overall network efficiency.

Once a station detects the channel to be busy, it initiates a random back-off process by generating a random back-off time within a CW size. The CW defines the range of possible back-off values. In this process, a slotted binary exponential back-off random interval is selected from the range of [0, CW], where CW initially starts with a minimum value of CW_{min}.

If a transmission attempt is unsuccessful, the CW value is doubled, resulting in a larger range of possible back-off values, up to a maximum value of CW_{max}. This doubling process continues with subsequent unsuccessful transmission attempts, allowing for increased back-off times and reducing the chances of collisions. On the contrary, a successful transmission results in the CW value being reset to its minimum value, CW_{min}. This reset aims to exploit the clear channel and ensure quick access to the medium for the station that successfully transmitted its data.

In other words, the random back-off procedure is defined to reduce the collision probability, energy consumption, and to allow fair access to the medium in a distributed manner, which can be controlled by initializing and changing the MAC layer parameters value. The selection of appropriate MAC layer values is crucial, not only for efficient channel access but

TABLE 1. Features comparison of related work and our proposal.

Studies \ Properties	Modification	AP coordination	QoS support	Energy harvesting	Energy optimization	Throughput optimization	ML approach	Compatibility with legacy	Year
Son et al. [15]	Dynamic AIFSN	✗	✓	✗	✗	✓	✗	✗	2016
Tian et al. [16]	BEB[1]	✗	✓	✗	✗	✓	✗	✗	2016
Syed et al. [17]	BEB	✗	✓	✗	✗	✓	✗	✗	2017
Chemrov et al. [18]	Improved PCA	✗	✓	✗	✗	✓	✗	✓	2022
Lin et al. [19]	Energy-based DCF	✗	✗	✓	✓[2]	✗	✗	✓	2015
Zhao et al. [20]	Random Sleeping Window	✗	✗	✓	✓	✗	✗	✓	2015
Kumar et al. [22]	Dynamic CW_{min}	✗	✗	✗	✗	✗	DRL	✓	2021
Guo et al. [23]	Adaptive time slot	✗	✓	✗	✗	✓	MARL	✓	2022
Cho [24]	Adaptive transmission rate	✗	✗	✗	✗	✓	RL	✓	2021
Koda et al. [25]	Beamforming	✗	✗	✗	✗	✗	DRL	✓	2019
Kotagiri et al. [26]	Distributed Resource Unit	✗	✗	✗	✗	✓	DQN	✓	2020
Luo et al. [27]	Channel bonding	✗	✗	✗	✗	✓	DQN	✓	2020
Krishnan et al. [28]	Distributed MIMO	✗	✗	✗	✗	✓	DDPG	✓	2019
Carrascosa et al. [29]	AP association	✗	✗	✗	✗	✓	MAB	✓	2019
Han et al. [30]	Handoff management	✗	✗	✗	✗	✓	DQN	N/A	2019
Bast et al. [31]	Slicing	✗	✗	✗	✗	✓	DQL	✓	2019
Ali et al. [32]	Scaled back-off	✗	✗	✗	✗	✓	QL	✗	2018
Famitafreshi et al. [33]	Optimal application-based CW	✓	✓	✓	✓	✗	✗	✓	2021
Our proposal	Dynamic MAC parameters	✓	✓	✓	✓	✗	RL	✓	2023

[1]Binary Exponential Back-off.
[2]The energy analysis is based on the energy consumption per successful transmission, but not total energy consumption.

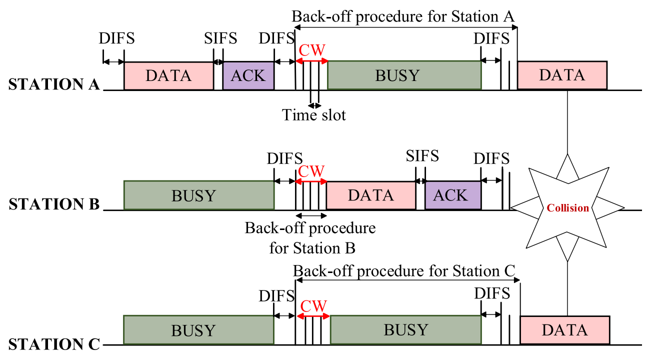


FIGURE 1. CSMA/CA back-off procedure.

TABLE 2. Quality of service requirements for e-Health applications.

Application Type	QoS Parameters			
	E2E Delay (ms)	**Packet Loss Ratio (%)**	**Jitter (ms)**	**Sensitivity to Context**
ECG [15], [36], [37]	<30	<10	25	✓
EEG [15], [36], [38]	<30	<10	25	✓
EMR [39], [40], [41]	< 100	<10	30	✗

also to minimize energy consumption related to collisions. For instance, a larger CW value reduces collisions and minimizes energy wastage associated with collision events, which is beneficial for energy efficiency. However, a larger CW value can also introduce increased delays in accessing the channel, potentially affecting QoS requirements, particularly for time-sensitive applications. On the other hand, a smaller CW value reduces delay but increases the probability of collisions and energy consumption. In addition, regarding other MAC layer parameters, such as AIFSN and TXOP, the system performance can be improved by adjusting these values. Reducing AIFSN values grants higher-priority frames a briefer back-off time, facilitating quicker transmission after the channel becomes idle. Modifying the TXOP permits consecutive transmission of multiple frames, minimizing the back-off and contention overhead. Thus, finding the right balance for the MAC layer parameters is crucial to optimize network performance, energy efficiency, and meeting the specific QoS restrictions imposed by the applications running on the network. Since IoT-based networks have a high level of collision probability, there is a need to apply modifications to the selection of these parameters and adjust them to the condition of the network and application types. However, these modifications have to be aligned with the standard and address the restricted QoS e-health environments.

Although ML algorithms have been introduced to improve the performance of Wi-Fi communication effectively, they mainly focus on increasing the throughput without considering the QoS requirement and energy efficiency of the network, which are necessary for the successful integration of EH techniques within Wi-Fi-based IoT systems. To fill the existing gap in the literature, in this article, we formulate the optimization problem based on three RL-based algorithms that are able to initialize different MAC layer parameters (i.e., initialization of CW values) dynamically based on the network condition and application traffic type while maintaining the two critical QoS parameters for QoS-restricted e-health applications known as E2E delay and PLR. The medical-grade QoS restrictions that are considered in this study are listed in Table 2.

Along with the high collision probability, unfair access to the medium, and increasing throughput requirement to meet the emerging applications (i.e., health-tracking wearable, 4k and 8k video streaming, VR or AR and gaming) provisions, such as ultra-reliable low-latency communication requirements and extremely high throughput, the channel access mechanism of the Wi-Fi MAC layer faces another concern for prioritizing and coordinating the transmissions. The extremely high throughput and

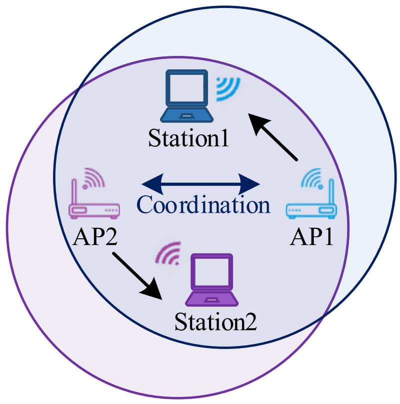


FIGURE 2. AP coordination concept.

ultra-low latency requirements listed above are beyond the capabilities of IEEE 802.11ax, even though the recently released IEEE 802.11ax emphasizes network performance and user experience in high-density deployment scenarios. IEEE 802.11ax only supports communication from a single AP and executes spatial reuse between APs and nodes without coordination among nearby APs. As a result, its ability to efficiently use time, frequency, and spatial resources is severely limited. In contrast, Wi-Fi 7 and Beyond with EHT capabilities improve this capability by allowing APs to share data and control information, increasing the throughput, reducing latency, and improving spectrum efficiency. Multi-AP coordination, which includes coordinated spatial reuse, coordinated orthogonal frequency-division multiple access, coordinated beamforming, and joint transmission, is one of the main differences between Wi-Fi 7 and Beyond and IEEE 802.11ax [14]. Therefore, to address these requirements, the upcoming amendment IEEE 802.11bn defines key concepts such as distributed multi-link operation, integrated mmWave operations, Physical (PHY) and MAC layer enhancement, and Multi AP coordination [42]. Among all these new features, controlling the delay of the system is possible based on AP coordination, which is a critical point for MIoT applications. The AP coordination technique states that to improve the performance of their associated non-AP stations, the so-called master APs can interact with other APs (slave APs) within their broadcast range. The master AP receives the beacon frames from the slave APs. The master AP might employ this technique to dynamically request the slave APs to rearrange the resources depending on the channel conditions (see Figure 2). While the need for uncoordinated systems is the main emphasis of this method, it is significant to emphasize that this strategy may also be used to coordinate systems [43].

In contrast to the aforementioned advantages of the concept of the AP coordination, it faces several issues when it comes to backward compatibility. The interoperability, influence on the network performance, implementation complexity, resource allocation, and overhead management are just a few of the new difficulties and challenges that come with AP coordination with backward compatibility. The functioning of AP coordination may cause interoperability issues when older devices find it difficult to interact with newer APs, resulting in decreased overall network performance, reliability, and efficiency, which can lessen the advantages of optimized performance of the current devices. The network's design and implementation may become more difficult, and additional management and configuration for overhead is needed if it supports both backward compatibility and advanced coordinating features. Furthermore, resource allocation for newer devices capable of handling more sophisticated coordination methods may be wasteful due to coordinating APs allocating resources based on the capabilities of old devices [44].

In this article, each group of nodes (i.e., non-AP stations) is associated with one respective AP in the assessed scenario. The main purpose of the proposed algorithms is to reduce the collision probability by differentiating the initialization of CW once per node and then per cell (i.e., all the nodes associated with their corresponding AP). However, per-node analysis increases the level of processing in the nodes, which can cause an increase in energy consumption. For this reason, centralized techniques are introduced to reduce the level of node processing. For example, the AP receives information about radio resource measurements of nodes [45]; therefore, the nodes with the low E2E delay increase their CW values to delay the data frame transmission.

In contrast, the nodes that exceed the medical-grade QoS threshold will reduce the CW to access the medium faster and immediately start the transmission. Furthermore, the agent makes decisions based on the remaining energy and E2E delay, which allows the node to harvest energy while maintaining medical-grade QoS requirements. In addition, the effect of the AP coordination concept is assumed in the proposed algorithms, in which APs are able to reschedule the resources based on the medium access conditions. Finally, a sleep/wake-up method is applied to obtain a higher level of energy reduction in the network.

IV. METHODOLOGY

This section utilizes RL-based optimization algorithms derived from Markov Decision Processes (MDP) to meet the proposed objectives of this paper.

In this study, MDP depicts the interaction between APs and nodes within a solar-based Wi-Fi, and it updates the decision-making in which an agent (AP) interacts with the environment. This framework models the optimization problem sequentially and is simplified as the following tuple.

$$(\Lambda, \Delta, \Gamma_a, \Phi_a) \tag{1}$$

where Λ is the representative of the group of states, which include the variables that define the environment or observation (in this paper, it corresponds to remaining energy, E2E delay, and PLR). Λ is updated at each step of the execution of the algorithms. Δ is the group of actions the agent executes in the AP, which is responsible for dynamic

Algorithm 1 Delay-Based Algorithm

Initialization: $\mathrm{CW_{min}} = 31, \mathrm{CW_{max}} = 1023$ Application-based QoS threshold
Input: Delay_node
Output: $\mathrm{CW_{new}}$_node
if Delay <= QoS Threshold **then**
  $\mathrm{CW_{new}} = ((\mathrm{CW_{current}} + 1) \times 2) - 1$
else if then
  $\mathrm{CW_{new}} = \left(\frac{\mathrm{CW_{current}}+1}{2}\right) - 1$
end if
return $\mathrm{CW_{new}}$
end procedure

Algorithm 2 Extremum-based AI algorithm.

Initialization: $\mathrm{CW_{min}} = 31, \mathrm{CW_{max}} = 1023$ Application-based QoS threshold
Input: Delay_node, RemainingEnergy_node
Output: $\mathrm{CW_{new}}$_node
for <nodes associated to the same AP> **do**
  <Sorting based on the node's remaining energy>
end for
if node with maximum remaining energy **then**
  if Delay <= QoS Threshold **then**
    $\mathrm{CW_{new}} = ((\mathrm{CW_{current}} + \alpha_{min}) - 1)$
  else if then
    $\mathrm{CW_{new}} = ((\mathrm{CW_{current}} - \alpha_{max}) - 1)$
  end if
end if
if node with minimum remaining energy **then**
  if Delay <= QoS Threshold **then**
    $\mathrm{CW_{new}} = ((\mathrm{CW_{current}} + \alpha_{\mathrm{max}}) - 1)$
  else if then
    $\mathrm{CW_{new}} = ((\mathrm{CW_{current}} - \alpha_{\mathrm{min}}) - 1)$
  end if
end if
return $\mathrm{CW_{new}}$
end procedure

changes of the MAC layer parameters (corresponding to the main operation of the proposed algorithms). $\Gamma_a(\Lambda^{t+1}|\Lambda^t, a)$ is the probability transition function depicting the probability of the action a (belongs to Δ) takes place in state t to reach state $(t+1)$ in the environment. Finally, Φ_a is the reward function, calculated after the execution of action a and updated at each step of the algorithm's execution to provide feedback for the decision-making in the next state [46], [47].

Each proposed algorithm highlights different decision-making methods for initializing MAC layer parameters. The first, second, and third sections address the initialization of MAC layer parameters for each node in the assessed scenario, where the CW values consider the primary parameter due to the random back-off procedure. Nevertheless, in Subsection IV-E, decisions are made based on the sleep/ wake-up mode. Additionally, in Subsection VI-D, we explore the effects of AIFSN and TXOP (considered as key MAC layer parameters) adjustments, alongside an evaluation of the CW adjustments. The difference between the proposed algorithms can be explained based on the level of the information that is fed to the APs to make decisions (i.e., only considering E2E delay or considering E2E delay and remaining energy). It is expected that the more information is considered, the level of optimization will be higher. In addition, the way that each algorithm selects the associated nodes to apply the dynamic changes of MAC layer parameters is different, which can be performed cell-wise or node-wise. In particular, in the case of CW values, it is expected that the differentiation in CW initialization reduces collision probability, addresses the medical-grade QoS requirement, and gives nodes with lower energy levels more opportunity to harvest energy. Aligning with the CW value changes the impact of the AIFSN and TXOP dynamic adjustments, as other MAC layer parameters need to be investigated.

A. DELAY-BASED ALGORITHM

The first proposed algorithm is the delay-based algorithm, which aims to reduce the collision probability of each node by delaying or accelerating the data transmissions in each node. This differentiation in initiating and selecting CW helps to avoid extra collisions due to the simultaneous transmissions. As explained in Algorithm 1, the agent (AP) checks the delay value for each node individually and makes decisions based on comparing the obtained E2E delay values with the defined corresponding medical-grade QoS threshold for each node at each time that the algorithm runs.

B. RANK-BASED EXTREMUM NODES ALGORITHM

In the second algorithm, the decision-making is made per cell to reduce the level of complexity and increase the residual energy at the node level. Then, within each cell, the algorithm selects the nodes with the extremum (i.e., the nodes with the minimum and maximum remaining energy) value of remaining energy, while the rest of the nodes store their current CW values and do not enter the following steps. According to Algorithm 2, the CW values are reduced by the factor of α ({2, 4, 8, 16}) if the delay of the extremum node exceeds the QoS requirement threshold. Otherwise, the α value is added to the current CW values. It is worth mentioning that the selection of the α value is in line with the IEEE 802.11 standard initialization of the CW values. This algorithm aims to assign different values of CW to the node to give the ones with the minimum energy the opportunity to harvest more energy and those with the maximum value of remaining energy to start the data frame transmission immediately.

C. RANK-BASED ALL NODES ALGORITHM

In contrast to the second algorithm, the decision-making is made at each node in the third one. In Algorithm 3,

Algorithm 3 Rank-Based All Nodes AI Algorithm

Initialization: $CW_{\min} = 31, \mathrm{CW}_{\max} = 1023$ Application-based QoS threshold
Input: Delay_node, Remaining Energy_node
Output: CW_{new}_node
for `<nodes within cell>` **do**
    `<sorting based on the node's remaining energy and select the median node>`
end for
if remaining energy_node > node with median remaining energy **then**
    if Delay <= QoS Threshold **then**
        $\mathrm{CW}_{\text{new}} = ((\mathrm{CW}_{\text{current}} + \alpha) - 1)$
    else if **then**
        $\mathrm{CW}_{\text{new}} = ((\mathrm{CW}_{\text{current}} - \alpha) - 1)$
    end if
end if
if remaining energy_node < node with median remaining energy **then**
    if Delay <= QoS Threshold **then**
        $\mathrm{CW}_{\text{new}} = ((\mathrm{CW}_{\text{current}} + \alpha) - 1)$
    else if **then**
        $\mathrm{CWnew} = ((\mathrm{CW}_{\text{current}} - \alpha) - 1)$
    end if
end if
return CW_{new}
end procedure

within the cell, the node with the median value of remaining energy keeps the CW values the same as its previous state. In comparison, the nodes with greater remaining energy than the median value slightly increase their delay duration if their delay lowers the QoS requirement. Otherwise, their CW values are decreased by the largest defined α values ($\{16,8\}$) to start the transmissions faster, differentiate the transmission's starting point, and reduce the collision probability.

In the opposite case, the nodes with the remaining energy values less than the median value need to increase their opportunity to harvest more energy for continuing the communication. The nodes with a delay less than QoS requirements increase the delay value by selecting larger CW values ($\alpha = 16,8$). On the contrary, although nodes have to start the transmission immediately to reduce the delay, the algorithm delays the communications for a short duration to allow them to harvest energy and begin the frame transmission while maintaining the QoS restrictions ($\alpha = 4,2$). Thus, in this algorithm, the agent allows all the nodes to differentiate the start of communication by initiating the CW values based on the condition of the channel and their remaining energy.

D. PROPOSED ALGORITHMS FOR AIFSN AND TXOP ADJUSTMENTS

While the RL-based algorithm designed for initializing CW values could be repurposed for adjusting other MAC layer parameters such as AIFSN and TXOP, it is essential to acknowledge the intrinsic differences between the CW and AIFSN, where AIFSN remains constant, whereas CW adjustments rely on random processes. Given this distinction, we have made subtle modifications to the algorithms to accommodate AIFSN adjustments. The node with an E2E delay less than QoS requirements updates its AIFSN value in the next window as follows.

$$AIFSN_{\text{new}} = AIFSN_{\text{old}} + 1 \tag{2}$$

where the initial value for AIFSN is considered as 2, and the maximum value is set to 15. We propose a strategy to prevent extended idle periods due to the maximum selection of AIFSN for all the nodes or the same value for all the nodes. AIFSN value increases until it is set to its maximum allowable limit and the E2E delay exceeds the QoS threshold. In this case, when the AIFSN reaches this maximum in a given window, it is then reset to its initial value in the following window. By resetting the AIFSN value to the initial value, we increase the level of randomness in AIFSN selection and prevent undesirable delay for all the nodes.

Shifting our focus to TXOP adjustment, the procedures mirror those outlined in Algorithms 1 to 3, ensuring consistent and coherent changes. If the node shows an E2E delay less than the QoS threshold, the transmission is delayed by increasing the idle listening duration.

$$TXOP_{\text{new}} = TXOP_{\text{old}} - 32 \tag{3}$$

By reducing the TXOP value, the duration a node requires to access the channel for transmission is diminished. This, in turn, allocates greater chances for other nodes to initiate their transmissions. It's worth highlighting that any alterations to the TXOP timing limit must occur in the multiple of 32 microseconds. The permissible range for TXOP values spans from 0 to 7.04 ms. However, in this case, when the E2E delay exceeds the QoS threshold, the TXOP value needs to gradually increase, and reduce the delay value. Selecting a large TXOP value for one node or setting it to the maximum value affects the network's fairness and gives other nodes less opportunity to start transmission. Thus, to prevent this behavior if the E2E delay of other nodes exceeds the limit, each algorithm reduces the TXOP of the node with the highest value of TXOP. In contrast to the AIFSN adjustment, higher TXOP values increase the idle listening duration for other nodes and violate network fairness.

E. SLEEP/WAKE-UP MODE

In this algorithm, to reduce the collision probability and improve the energy efficiency of the network, instead of differentiating the CW values in the proposed RL-based

Algorithm 4 Sleep/Wake-Up Method

Initialization: $CW_{\min} = 31, CW_{\max} = 1023$ Application-based QoS threshold
Input: Delay_node
if Delay >= QoS Threshold **then**
  node is forced to sleep
else if then
  Trigger the proposed RL-based algorithms
end if
end procedure

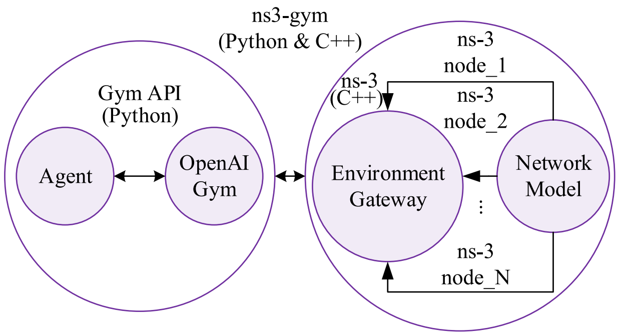


FIGURE 3. The general framework of the integration of RL with ns-3.

optimization algorithms, the selected nodes are forced to sleep mode, which will determine the starting time of the frame transmission of nodes (see Algorithm 4). The sleep/wake-up method procedure is detailed in [35]. This method mimics intermittent communication [48] when the communication is interrupted due to insufficient energy to keep the system powered up or a high level of interference in the channel.

V. SIMULATION SETUP

In this section, the system model and experimental environment to implement a dense solar-based Wi-Fi network in field hospital circumstances in the ns3-gym environment are described in detail. Then, the evaluation metrics are explained. This simulation setup allows us to assess the proposed RL-based optimization algorithms under specified conditions. Section VI will evaluate and discuss these algorithms.

A. SYSTEM MODEL

The proposed RL-based optimization algorithms are deployed in the ns3-gym framework, which consists of three main components, known as ns-3 simulator, OpenAI Gym, and ns3-gym middleware (see Figure 3).

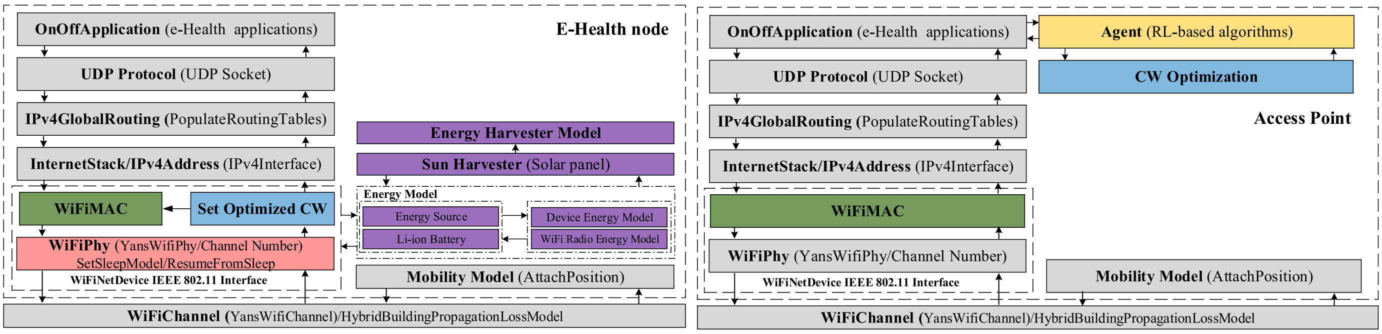
The ns-3 simulator is an open-source network simulator that mimics real-world constraints and provides features that need to be accomplished to meet IoT requirements [49], [50]. According to Figure 3, the ns-3 simulator is considered as an actual deployment of a solar-based dense Wi-Fi network in ns-3 (environment), and the E2E delay, PLR, remaining energy, and consumed energy are extracted from it (observation parameters). Since the reward function returns a numerical value as feedback to the action, the agent is able to make the most optimal decision based on this value. Here, the defined objective function (see Equation 4) is maximized based on the reward function feedback, where the remaining energy is maximized, and the E2E delay and PLR values are minimized.

$$\text{Objective Function} = \frac{\text{Remaining energy}}{\text{E2E delay} \times \text{PLR}} \tag{4}$$

The protocol level implementation of ns-3 Wi-Fi solar-enabled nodes is highlighted in Figure 4. The purple blocks correspond to components of energy-harvesting modules that have been integrated into the node. These modules define the type of source of energy (battery or a capacitor), Wi-Fi radio energy model, and device energy model. The device energy model locates the Wi-Fi radio energy model in each node for calculating the energy consumption of each state of transmission or the total energy consumption of the node [51]. It is worth mentioning that the solar energy harvester model, designed in [52], is appended to the energy-related model since the official version of ns-3 does not include this module. This implementation closely mimics the real behavior of a solar energy harvester that takes into account various aspects of the harvesting process in the ns-3 solar harvesting system. This technology realistically develops a solar panel and mathematically calculates many solar features influencing energy harvesting.

Along with the energy-related modules added to the ns-3 architecture, the proposed algorithms directly impact the initialization of the MAC layer parameters, shown in the green and blue blocks. These blocks describe the Wi-Fi MAC layer protocol implementation we adapt during the simulation. Another module that affects the MAC layer operation is the PHY layer, shown by the pink block. This block defines the different transmission states of the communication, where the sleep/wake-up method is defined to reduce the contention, which directly impacts the MAC layer [35]. The architecture of an AP in ns-3 is illustrated in Figure 4b, where the optimization problem is formulated, and the AP coordination concept is introduced (the blue block). In addition, the MAC layer modification commands and initialization values are sent to the nodes from the APs that the agent controls based on actions (the green block). Moreover, the PHY layer generates the sleep/wake-up commands triggered by the AP. Here, the APs decide when and which node has to go to sleep or wake-up mode. It is noted that no changes or modifications are applied to the gray-scale blocks.

The second part of the n3-gym is the ns3-gym middleware, which sends the gathered information to the environment gateway entity for saving the numerical data in a structured manner and encoding the received actions from the agent to numerical data. In addition, ns3-gym middleware receives the



(a) Architecture of a sensor node in ns-3.

(b) Architecture of an AP in ns-3.

FIGURE 4. Ns-3 IEEE 802.11 architecture to support RL algorithm and EH.

environment information (i.e., observation) and sends it to the agent.

The third part of the ns3-gym framework is the OpenAI Gym, which fundamentally is a toolkit capable of creating new ML algorithms in a range of simulated environments. The Python process, consisting of the agent and the Gym environment, establishes communication with the C++ process, responsible for the ns-3 network simulation, through ZMQ sockets. Readers interested in learning more about the OpenAI Gym are referred to [53].

B. ENERGY MODEL FOR THE CONSIDERED WI-FI SCENARIO

Various components contribute to the overall energy consumption of Wi-Fi systems. Yet, achieving an exact calculation of the total energy consumption proves intricate, owing to the dynamic characteristics of wireless channels, the complexity of the Wi-Fi protocol, and the fluctuations in network traffic patterns. This section delves into a simplified explanation of the total energy consumption within the specific Wi-Fi scenario under consideration.

The total energy consumption of the Wi-Fi system corresponds to the sum of the energy consumption during the fundamental states, such as transmission, reception, transition, idle, and back-off states, which is formulated as follows.

$$E_{\text{Total}} = \sum_{i=1}^{m} \big(E_{\text{Tx(m)}} + E_{\text{Rx(m)}} + E_{\text{Idle(m)}} + E_{\text{Transition(m)}} + E_{\text{Back-off(m)}}\big) \tag{5}$$

where

$$\begin{aligned} E_{\text{Tx}} &= E_{\text{Ack-tx}} + E_{\text{Data-tx}}, \\ E_{\text{Rx}} &= E_{\text{Ack-rx}} + E_{\text{Data-rx}}, \\ E_{\text{Transition}} &= E_{\text{Sleep}} + E_{\text{Wake-up}}, \\ E_{\text{Back-off}} &= E_{\text{BO}} + E_{\text{Collision}} \end{aligned}$$

In this case E_{Tx}, E_{Rx}, $E_{\text{Transition}}$ correspond to the energy consumption in the transmission state, reception state, and changing from sleep mode to wake-up or vice versa. In addition, this formula considers the energy consumption during the back-off procedure ($E_{\text{Back-off}}$), which includes initialization of the CW procedure and collision. Here, m refers to the number of the stations in the network. Furthermore, each component can be decomposed as the multiplication of the power and duration of that state as follows.

$$\begin{aligned} E_{\text{Tx}} &= P_{\text{Ack-tx}} \times T_{\text{Ack-tx}} + P_{\text{Data-tx}} \times T_{\text{Data-tx}}, \\ E_{\text{Rx}} &= P_{\text{Ack-rx}} \times T_{\text{Ack-rx}} + P_{\text{Data-rx}} \times T_{\text{Data-rx}}, \\ E_{\text{Idle}} &= P_{\text{Idle}} \times T_{\text{Idle}}, \\ E_{\text{Transition}} &= P_{\text{Sleep}} \times T_{\text{Sleep}} + P_{\text{Wake-up}} \times T_{\text{Wake-up}}, \\ E_{\text{Back-off}} &= P_{\text{BO}} \times T_{\text{BO}} + P_{\text{Collision}} \times T_{\text{Collision}} \end{aligned}$$

According to the EDCA mechanism, the duration of the acknowledgment, successful data frame transmission, idle [54], back-off procedure, and collision are defined as follows.

$$\begin{aligned} T_{\text{Ack}} &= DIFS + T_{\text{Slot}} + SIFS, \\ T_{\text{Data}} &= DIFS + T_{\text{Slot}} + SIFS + T_{\text{Ack}}, \\ T_{\text{Idle}} &= AIFS, \\ T_{\text{BO}} &= (CW - 1) \times T_{\text{Slot}}, \\ T_{\text{Collision}} &= SIFS + T_{\text{Ack}} + AIFS \end{aligned}$$

It is important to mention that the energy consumption during the frame retransmission is considered in the $E_{\text{Collision}}$, in addition, the sleep and wake-up duration could vary based on the specific AC and power-saving settings that is considered in the algorithm.

In line with the total energy consumption formula and aforementioned analysis, an inverse relationship exists between the CW and total energy consumption ($\frac{1}{\text{CW}} \propto E_{\text{Total}}$). As the CW value decreases, the duration before transmission becomes shorter. This reduction in waiting time leads to increased transmission attempts due to more active states and potential retransmissions, ultimately resulting in elevated energy consumption.

A simulation-based decomposition of the energy consumption of the network is analyzed in [35], where the E_{Tx},

E_{Rx}, E_{Idle}, $E_{\text{Transition}}$ and $E_{\text{Back-off}}$ states consumed 0.5 J, 3.42 J, 9.02 J, 1.02 J, and 0.63 J, respectively. According to the analyzed energy model, the network's total energy consumption equals 14.59 J, and each node consumes 0.364 J in the system. In this paper, we examine all the MAC layer parameters outlined in Equation 5, encompassing not only those mentioned but also encompassing wake and sleep states.

C. NETWORK SCENARIO DEFINITION AND EVALUATION METRICS

The simulation environment is a one-floor field hospital (similar to an office-type building) with an area of 3200 m^2 and 3 m of the height of the floor. According to Figure 5, this area is divided into 8 symmetric rooms (each room area is 20 m $\times$ 20 m). The rooms are separated through wooden walls (brown lines), and the external walls are defined as concrete walls with windows (black bars). The simulations were carried out using the hybrid building propagation model, which provides the required flexibility to represent the Wi-Fi implementation in a building environment. This model includes several factors, such as the frequency in use, the environments (urban, suburban, or rural), International Telecommunication Union defined path loss model [55], the position of the interfering nodes, external wall penetration loss of different types of buildings (such as windows, without windows, concrete among others), and the internal wall loss. All of the factors mentioned above, among others, are used to derive the indoor path loss, which is used along with the transmit signal power to derive the received signal power. By design choice, we consider a single AP per room, in which one AP is located in the middle of the room, and 5 nodes are placed randomly within the room. The distance between the AP and each node is randomly selected from 1 to 10 m. This article considers the worst-case scenario of Wi-Fi communication, where the 2.4 GHz frequency band is used for communications. The restricted bandwidth of 2.4 GHz, with only three non-overlapping channels, causes high interference, and due to the few non-overlapping channels, the 2.4 GHz frequency can become congested quickly. For this reason, the main issue of contention-based communications in the 2.4 GHz frequency band is the high collision probability.

It is important to note that we have employed IEEE 802.11n in the simulated scenario. This choice ensures that the scenario that has been discussed here aligns precisely with the enterprise model outlined in the IEEE 802.11ax standard and described in [59]. Furthermore, most assessments of Wi-Fi 7 and Beyond follow the operational guidelines established by the IEEE 802.11ax Working Task Group. This is because the development of Wi-Fi 7 builds upon discussions held with Task Group ax(TGax), essentially serving as an extension of those conversations.

To evaluate the performance of the proposed RL-based optimization algorithms in each set of simulations, we consider 8 AP (triangles in Figure 5) and nodes associated with each one (red circles). In addition, the master APs are illustrated as green triangles and the slave APs as blue triangles. Each node uses three medical applications in the simulations: ECG, EEG, and EMR (representing medical file transferring). For the final results, each set of simulations is repeated 20 times with different seed values (to add randomness to the implementation) to increase the confidence level.

The parameters of the PHY and MAC layers are listed in Table 3 and Table 4. Since the Request to Send (RTS)/Clear to Send (CTS) mechanism (the four-way handshaking mechanism) increases the transmission time inherently, and a non-optimal frame aggregation can increase the error rate,

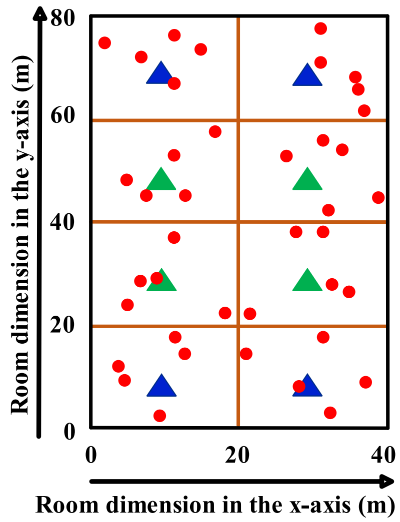


FIGURE 5. Layout of the Wi-Fi deployment in the field hospital.

TABLE 3. PHY layer parameters for the simulation.

Parameter	Value
Wireless Standard	IEEE 802.11n
Frequency band	2.4 GHz
Physical transmission rate	MCS 5 for data frames
Physical transmission rate	MCS 0 for control frame
Propagation loss model	Hybrid building propagation loss
External Wall penetration loss	7 dB
Internal Wall penetration loss	4 dB
Transmission power	16 dBm
Energy detection threshold	−62 dBm
CCA model threshold	−82 dBm
Guard interval	Short
Channel bandwidth	20 MHz
Channel Number	1
Number of the AP	8
Stations per AP	5

TABLE 4. MAC layer parameters for the simulation.

Parameter	Value
Default CW_{min}	31
Default CW_{max}	1023
AIFS	3 μs
TXOP	0 ms
RTS/CTS	Disabled
MSDU aggregation	Disabled
MPDU aggregation	Disabled

TABLE 5. Traffic characteristics in the simulation study.

Traffic Type	ECG	EEG	EMR
Access Category	BE	BE	BE
Traffic model	ON-OFF (0.650–0.350) CBR [56]	ON-OFF (0.29–0.71) CBR [15]	ON-OFF (0.05–0.95) Exponential [15]
Data rate	12 kbps [57]	32 kbps [58]	4.1 Mbps [15]
Packet size (Bytes)	147 [15]	155 [58]	1528 [15]

as is shown in Table 4, frame aggregation and RTS/CTS are disabled. The default MAC layer parameters are selected as the Best Effort (BE) Access Category (AC) corresponding to the traffic model of the three medical applications. Only the CW values change dynamically in this paper, and AIFSN and TXOP are maintained constant. It is noted that during the MAC layer modifications, all the parameters of the PHY layer are kept constant according to Table 3.

Table 5 summarizes the traffic model, data rate, and packet size for ECG, EEG, and EMR applications as the selected medical applications.

The Li-Ion battery and the panel dimension (corresponding to the size of a remote blood oxygen monitoring [60]) are adopted from [35]. The metrics for the evaluation are defined based on their equations in Table 6.

This setup allows us to explore the performance of our proposed RL-based algorithms by automatically varying the CW values as a MAC parameter for nodes based on the current condition of the channel and then with the offered sleep/wake-up method.

VI. PERFORMANCE EVALUATION AND DISCUSSION

In this section, through extensive ns3-gym-based simulations, we evaluate the performance of the proposed RL-based optimization algorithms in the selected environment. The performance evaluation analysis first focuses on CW value changes to define the usefulness and assess the proposed RL-based algorithms. In Section VI-D, we investigate the impact of other MAC layer parameters on the performance of the network. For this reason, we will use a consistent EDCA queue, denoted as EMR, to assess the effects of altering various MAC layer parameters. Subsequently, we will contrast the outcomes with those of a system adhering to default values (Tabel 4). This clarification will be explicitly presented in Section VI-D. As highlighted in Section III, to manage the network resources more efficiently and decrease E2E delay in this scenario, the concept of AP coordination will be introduced to the proposed algorithms and evaluated in this section. In this study, the master and slave cells are distinguished based on their Frame Error Rate (FER).

A. COMPARISON OF LEGACY WITH THE PROPOSED ALGORITHMS FOR CW ADJUSTMENT

Previous studies indicated that there is an optimal value for initializing CW for a node that can retain the collision probability at the lowest possible level and, as a result, reduces energy consumption while maintaining the E2E latency and PLR metrics below the medical-grade QoS requirements [35]. Additionally, this optimal value varies depending on the application and traffic types and the condition of the network. Therefore, it is necessary to dynamically assign an optimal CW value to each node in IoT-based networks to prevent long E2E delays and high collision probability. It is expected that such a scenario will benefit from RL algorithms. In each algorithm initially the CW_{min} and CW_{max} values are set to the default values (see Table 4). Then, these values are selected based on the received information from the environment.

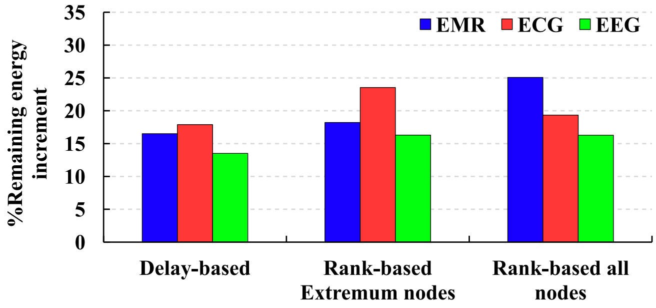


FIGURE 6. Legacy comparison with the proposed algorithms under CW adjustment for medical applications.

Figure 6 illustrates the improvement of remaining energy by applying the RL algorithms in the Wi-Fi-based IoT system for medical applications. While the rank-based all-nodes algorithm, when used for EMR application, increases the energy efficiency up to 26.5% (from 14.68 J to 18.36 J), it reduces the E2E delay, PLR (15.87 ms and 2.4%receptively), ECG, and EEG applications benefit more from the rank-based extremum nodes algorithm. Where the remaining energy improves up to 23.5% and 16.2% (4 and 3 J improvement per application), delay reduces to 9 and 3 ms for ECG and EEG applications, respectively (PLR is negligible in ECG and EEG applications). The results are shown in Table 7 can be explained by differentiating the CW values initialization among nodes based on the traffic model characteristics. As indicated in Figure 7, the selected CW values are relatively large in the delay-based algorithm, which increases the network delay considerably and consumes more energy. However, since the CW values initialization is more distributed among all possible intervals in the rank-based all-nodes algorithm, it has a better adaptation to the network condition. Consequently, it can save more energy for applications with high data rates and large packet sizes, such as EMR applications. In contrast to the high-traffic load applications, the applications with low traffic load levels benefit the rank-based extremum nodes algorithm with a lower level of complexity.

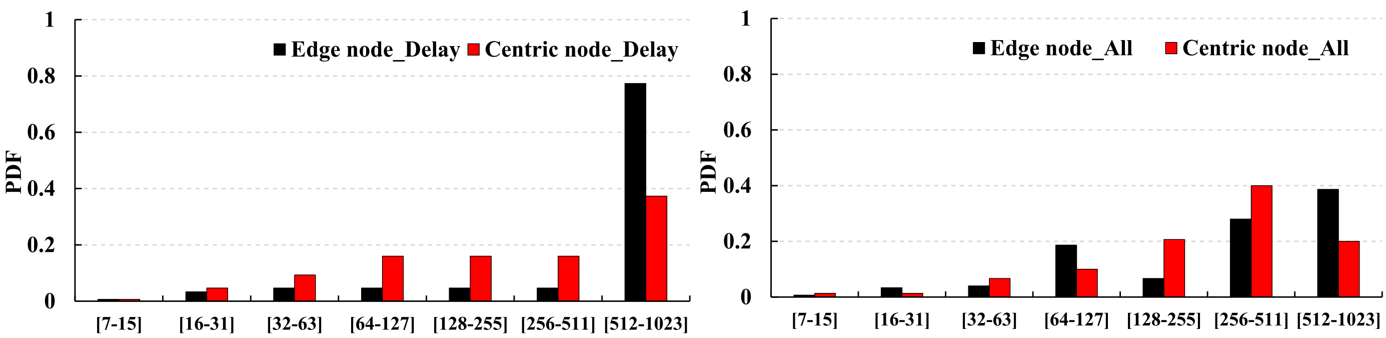
B. COMPARISON OF LEGACY WITH THE PROPOSED ALGORITHMS UNDER AP COORDINATION ASSUMPTION FOR CW ADJUSTMENT

In this set of simulations, we evaluate the impact of the AP coordination concept on the performance of the network with

TABLE 6. Metrics for evaluation.

Metric	Definition	Equation	Reference
E2E delay	Starts by generating the frame from the source until it reaches its destination	$D_{\mathrm{Tx}} + D_{\mathrm{queuing}} + D_{\mathrm{contention}}$	[61]
Remaining energy	Includes initial energy of a Li-Ion battery and total harvested energy subtracted by the consumed energy	$\mathrm{E}_{\mathrm{Initial}} + \mathrm{E}_{\mathrm{Harvested}} - E_{\mathrm{Consumption}}$	[35]
PLR	Number of lost packets in the transmission procedure[3]	$1 - PDR$	[35]
FER	Number of lost frames in the transmission procedure[4]	$1 - FSR$	[11]

[3]Packet Delivery Ratio (PDR) is the number of the packets that are received successfully.
[4]Frame Success Rate (FSR) is the number of the acknowledged frames divided by the total transmitted frame.



(a) Delay-based algorithm. (b) Rank-based all-nodes algorithm.

FIGURE 7. Probability Density Function for CW changes for the proposed RL-based algorithms.

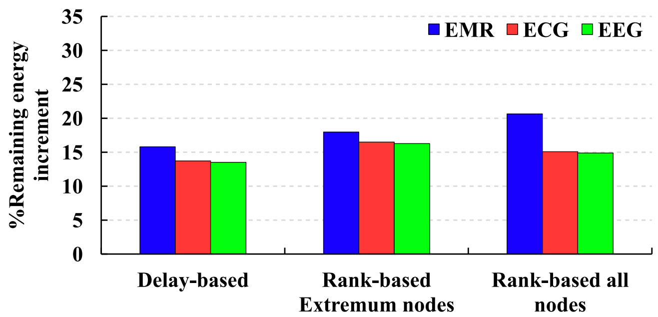


FIGURE 8. Impact of master cells AP coordination on the proposed algorithms under CW adjustment.

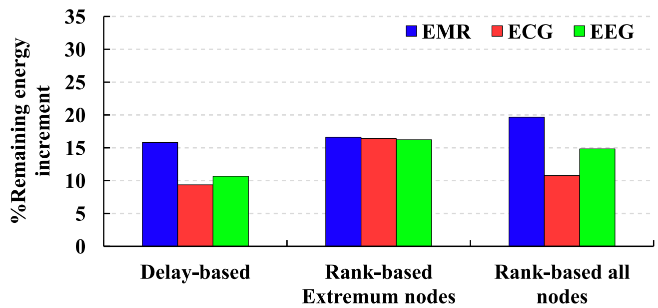


FIGURE 9. Impact of slave cells AP coordination on the proposed algorithms under CW adjustment.

three proposed RL-based optimization algorithms. If the cell has a FER value greater than the average FER of the network, it is considered the master cell, otherwise, it is deemed a slave cell.

For this scenario, the proposed algorithms are deployed only at the master cells. As illustrated in Figure 8 the system faces improvements in the evaluated metrics compared to the legacy in all the cases. However, the improvement percentage is less than the case where we implement three algorithms in all the cells (cf. Table 7). The logic behind the obtained results can be explained through the differentiation of the initialization in the CW values for central and edge nodes, where the master cells (located as central nodes) face more variation in the initialization of the CW values. However, for the nodes in the slave cell, the initialization is fixed to the default values. The results prove that more variation in the initialization of the CW values based on the network condition can improve the energy efficiency of the network while reducing the QoS parameters such as delay and PLR.

In the following scenario, when the proposed algorithms are applied to the slave cells, the obtained results demonstrate a lower improvement level than the previous results. Regardless of the network conditions, the initialization of the CW values for the nodes in the center (which face more collisions) is fixed as the default values. Therefore, the network reaches at most 19.60% remaining energy improvement for EMR application in the case of the rank-based all-nodes algorithm, 16.40%, and 16.23% in the case of ECG and EEG application under the deployment of the rank-based extremum nodes algorithm (see Figure 9).

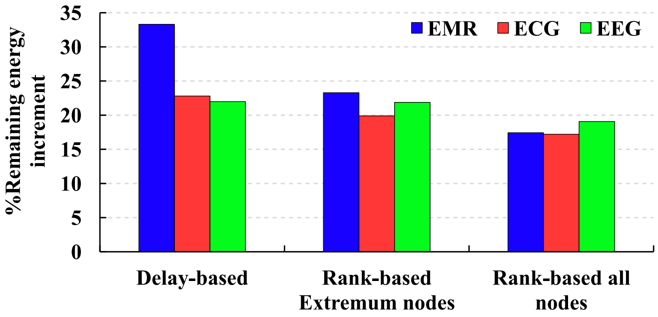


FIGURE 10. Impact of sleep/wake-up method on the proposed algorithms.

It can be concluded that when the proposed algorithms are only applied to a group of cells in the AP coordination, although the E2E delay can be controlled through the AP coordination concept, the fixed CW initialization for the other group of cells can degrade the network's overall performance. For this reason, the overall network improvement is smaller than when the proposed algorithms are applied to all the nodes. It can be perceived from Table 7 improvements are less than 1 J for the remaining energy metric for all the applications regardless of whether the AP coordination is deployed in master or slave cells.

In the following set of simulations, to reduce the collision probability, and consequently, increase the remaining energy, instead of differentiating the CW initialization on the nodes, the algorithms will force the node to go to sleep.

C. COMPARISON OF LEGACY WITH THE PROPOSED ALGORITHMS UNDER SLEEP/WAKE-UP METHOD

In this set of simulations, we introduce the sleep/wake-up method (introduced in [35]) to our proposed algorithms. In this case, the algorithm restricts the node to transmit, with a condition that the E2E delay does not exceed the set QoS threshold. Therefore, the sleeping node has the opportunity to harvest energy and then, in the next time step, follows the procedure of the proposed RL-based optimization algorithm. According to Figure 10, all the proposed algorithms improve the energy efficiency for the three selected applications. Although E2E delay values are still under the QoS threshold, these values increase considerably compared to the previous evaluation. In some cases, such as the rank-based extremum nodes algorithm for EMR, the E2E delay exceeds the threshold. In contrast to the earlier cases, the highest remaining energy level while keeping the QoS values at the desired level corresponds to the delay-based algorithm (cf. Table 7), where the system is able to conserve energy around 4 J for ECG and EEG applications and 5 J for EMR application. The reason is the simplicity of the procedure of the algorithm, which makes decisions faster than the other algorithms. Finally, the node can harvest more energy in a shorter duration.

TABLE 7. Impact of proposed algorithms on network metrics.

		ECG	EEG	EMR
Legacy Wi-Fi	**Remaining energy (J)**	17.89	18.10	14.68
	E2E Delay (ms)	18.75	7.81	36.01
	PLR (%)	3.9	1.5	32.5
	Objective Function	2.5	15.45	0.125
(a) Three algorithms				
Delay-based	**Remaining energy (J)**	21.1	20.54	17.10
	E2E Delay (ms)	17.89	4.86	21.57
	PLR (%)	<0.05	<0.05	29.82
	Objective Function	3.03	26.66	0.265
Rank-based extremum nodes	**Remaining energy (J)**	**21.05**	**22.11**	17.35
	E2E Delay (ms)	**9.64**	**3.06**	34.46
	PLR (%)	<0.05	<0.05	27.6
	Objective Function	**5.05**	**72.43**	0.182
Rank-based all nodes	**Remaining energy (J)**	21.36	21.04	**18.36**
	E2E Delay (ms)	12.19	4.44	**15.87**
	PLR (%)	<0.05	<0.05	**23.92**
	Objective Function	2.79	52.81	**0.483**
(b) AP coordination in master cells				
Delay-based	**Remaining energy (J)**	20.35	20.54	17
	E2E Delay (ms)	17.11	4.74	29.07
	PLR (%)	<0.05	<0.05	29.4
	Objective Function	6.96	22.90	0.198
Rank-based extremum nodes	**Remaining energy (J)**	**20.85**	**21.04**	17.32
	E2E Delay (ms)	**8.81**	**3.48**	29.07
	PLR (%)	<0.05	<0.05	27.4
	Objective Function	**3.41**	**42.88**	0.217
Rank-based all nodes	**Remaining energy (J)**	20.59	20.79	**17.71**
	E2E Delay (ms)	15.85	4.74	**24.45**
	PLR (%)	<0.05	<0.05	**27.6**
	Objective Function	1.12	32.72	**0.262**
(c) AP coordination in slave cells				
Delay-based	**Remaining energy (J)**	19.57	20.03	16.11
	E2E Delay (ms)	17.75	4.74	21.57
	PLR (%)	<0.05	<0.05	29.82
	Objective Function	6.18	18.22	0.25
Rank-based extremum nodes	**Remaining energy (J)**	**20.83**	**21.03**	17.11
	E2E Delay (ms)	**9.64**	5.23	34.46
	PLR (%)	<0.05	<0.05	27.6
	Objective Function	**5.03**	**63.54**	0.179
Rank-based all nodes	**Remaining energy (J)**	19.82	20.78	**17.56**
	E2E Delay (ms)	12.9	**4.44**	**25.85**
	PLR (%)	<0.05	<0.05	**23.92**
	Objective Function	1.14	25.68	**0.702**
(d) Sleep/Wake-up method				
Delay-based	**Remaining energy (J)**	**21.97**	**22.08**	**19.57**
	E2E Delay (ms)	**38.42**	**27.72**	**87.67**
	PLR (%)	<0.05	<0.05	**9.67**
	Objective Function	1.74	12.53	**0.231**
Rank-based extremum nodes	**Remaining energy (J)**	21.45	20.06	18.1
	E2E Delay (ms)	39.99	12.42	103.99
	PLR (%)	<0.05	<0.05	11.55
	Objective Function	**4.43**	**27.41**	0.150
Rank-based all nodes	**Remaining energy (J)**	20.97	21.55	17.24
	E2E Delay (ms)	34.8	15.34	92.63
	PLR (%)	<0.05	<0.05	33.5
	Objective Function	2.24	13.02	0.055

D. COMPARISON OF LEGACY WITH THE PROPOSED ALGORITHMS FOR AIFSN AND TXOP ADJUSTMENTS

As discussed in Section I, the EDCA mechanism prioritizes channel access through three key parameters: CW, AIFSN, and TXOP, aiming to deliver the necessary QoS for diverse applications. This series of simulations showcases the individual impacts of these parameters on network performance. The algorithms under examination dynamically select CW, AIFSN, and TXOP, each addressed separately, to pursue this goal.

According to the EDCA framework, a lower AIFSN value signifies elevated traffic priority for channel access. However, unsuitable AIFSN adjustments can compromise QoS regarding E2E delay, fairness among stations, and diminishing overall network throughput. Reduced AIFSN intensifies contention dynamics, fostering potential collisions, while

TABLE 8. Impact of MAC parameters changes on the proposed algorithms.

		ECG	EEG	EMR
Legacy Wi-Fi	Remaining energy (J) E2E Delay (ms) PLR (%)	17.89 18.75 3.9	18.10 7.81 1.5	14.68 36.01 32.5
(a) Three algorithms_CW				
Delay-based	Remaining energy (J) E2E Delay (ms) PLR (%)	21.1 17.89 <0.05	20.54 4.86 <0.05	17.10 21.57 29.82
Rank-based extremum nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	**21.05** **9.64** <0.05	**22.11** **3.06** <0.05	17.35 34.46 27.6
Rank-based all nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	21.36 12.19 <0.05	21.04 4.44 <0.05	**18.36** **15.87** **23.92**
(b) Three algorithms_AIFSN				
Delay-based	Remaining energy (J) E2E Delay (ms) PLR (%)	16.06 27.41 2.5	17.28 24.76 2.5	15.66 29.61 31.02
Rank-based extremum nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	**17.09** **24.6** 2.5	**18.03** **23.14** 2.5	16.85 35.42 30.5
Rank-based all nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	16.11 26.11 2.5	17.27 25.74 2.5	**17.58** **19.61** **28.61**
(c) Three algorithms_TXOP				
Delay-based	Remaining energy (J) E2E Delay (ms) PLR (%)	15.07 28.61 2.5	16.28 25.93 2.5	12.06 58.56 46
Rank-based extremum nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	**16.07** **25.16** 2.5	**17.07** **24.18** 2.5	12.67 52.42 45
Rank-based all nodes	Remaining energy (J) E2E Delay (ms) PLR (%)	15.9 28.64 2.5	16.27 27.75 2.5	**13.46** **49.65** **40**
(d) Fine-tuning MAC layer parameters				
MAC fine-tuning	Remaining energy (J) E2E Delay (ms) PLR (%)	23.02 11.08 <0.05	23.8 13.25 1.2	20.12 32.28 30.5

higher values lead to extended idle periods and channel under-utilization. Thus, as explained in subsection IV-D, it is necessary to set a proper AIFSN value for each individual node. This phenomenon is corroborated by the findings in Table 8, revealing decreased remaining energy due to prolonged idle duration and increased collisions, which is less than 1 J reduction in remaining energy for ECG and EEG applications. In the case of E2E delay, this reduction shows 15 ms for ECG and EEG applications. However, this energy reduction is marginal when compared with legacy values. In the case of the EMR application, a proper AIFSN value conserves the energy of the network around 3 J by reducing the E2E delay for 16.4 ms.

Regarding dynamic TXOP, a station granted a TXOP can transmit frames consecutively without inter-frame channel contention. This enhances throughput efficiency within the station's allocated time window. Nonetheless, this increased throughput for one station can hinder other stations' channel access, resulting in extended idle periods and decreased overall throughput, surpassing the fairness issues attributed to inappropriate TXOP selection. This behavior is depicted in Figure 11 to Figure 13, where dynamic TXOP RL-based algorithms exhibit the lowest remaining energy values, in contrast to the dynamic initialization of CW values, which result in the highest remaining energy values. According to Table 8 the remaining energy values under TXOP RL-based algorithms decrease more than 1 J per application. Here, the legacy value is illustrated as a straight dotted line that

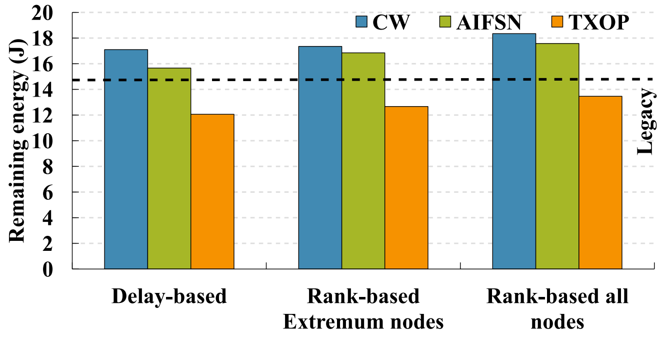


FIGURE 11. Impact of MAC layer dynamic changes on remaining energy for EMR application.

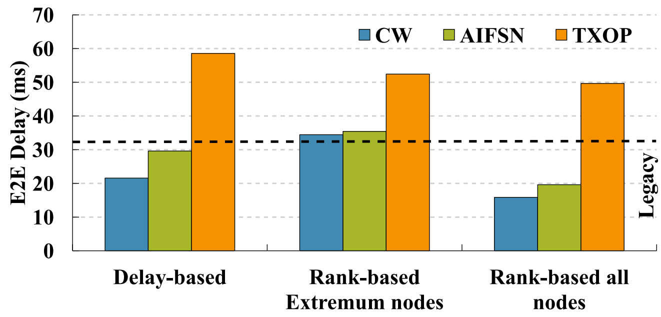


FIGURE 12. Impact of MAC layer dynamic changes on E2E for EMR application.

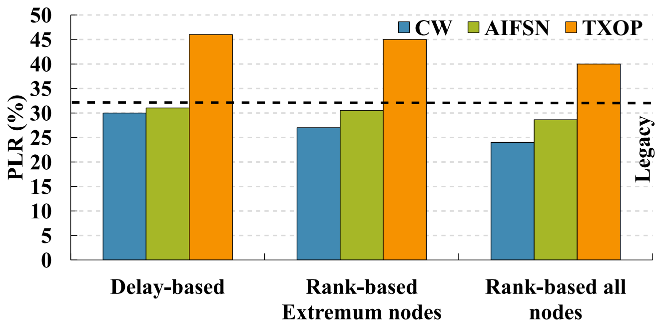


FIGURE 13. Impact of MAC layer dynamic changes on PLR for EMR application.

indicates the values achieved by the legacy network, in which all devices use the default MAC layer parameters without ML adaptation. These values are listed in Table 4. These outcomes underscore the need for more comprehensive network metrics when making AIFSN and TXOP adjustments. It is important to note that, since the changes are more considerable in the case of the EMR application, we only visualize the impact of the MAC layer parameters in network metrics, and the rest of the metric comparisons can be found in Table 8.

Notably, although TXOP dynamics reduce remaining energy, E2E delay remains within QoS requirements, which means less than 30 ms for ECG and EEG applications and less than 100 ms for EMR application. This implies the efficacy of the proposed algorithms in such scenarios for these three MAC layer parameters. However, these algorithms demand more comprehensive information (more network metrics) for

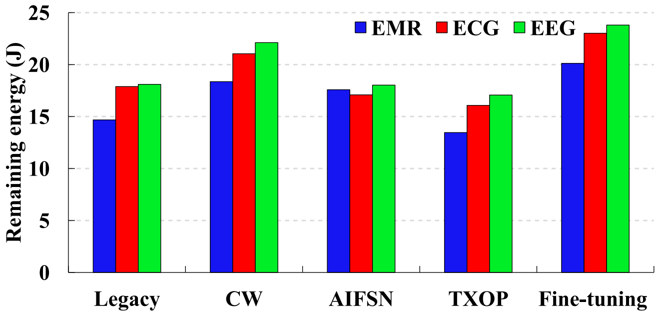


FIGURE 14. Remaining energy actual values comparison per application.

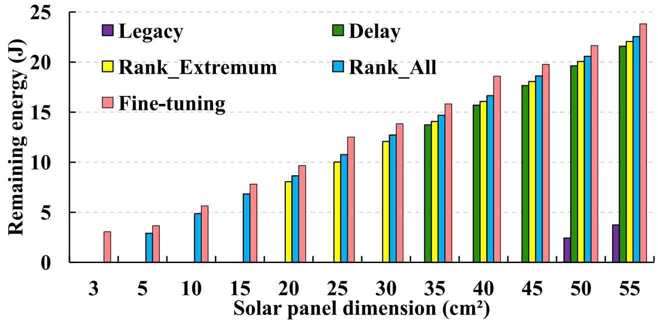


FIGURE 15. Impact of the proposed algorithms on the solar panel form factor.

enhanced decision-making accuracy. Consequently, dynamic CW initiation proves more effective within the current scenario.

Drawing upon the results deriving from the proposed RL-based optimizations at the MAC layer, the finest configuration for individual MAC parameters becomes achievable and tailored to each application's unique demands. Within the simulations, these optimal values are considered when notable enhancements in system performance arise, particularly evident in conserving the network's total energy exceeding 5 J for ECG and EEG while staying below 5 J for EMR scenarios. Nevertheless, the E2E delay increased slightly from the CW adjustment results due to the AIFS duration increase.

To facilitate a more comprehensive comparison of remaining energy among the legacy MAC layer parameters, the proposed RL-based algorithms, and the optimized MAC layer parameters, we visually present the actual remaining energy values per application in Figure 14. As previously noted, the fine-tuned MAC layer parameters outperform other cases through the most energy-efficient configuration.

E. IMPACT OF THE PROPOSED ALGORITHMS ON THE SOLAR CELL FORM FACTOR

According to the literature, since solar cells, piezoelectric, and thermoelectric harvesters provide a more reliable and higher power density level for indoor environments (100 mW/cm^3, 2 W/cm^3, 50 mW/cm^3 for solar cell, piezoelectric, and thermoelectric, respectively), they are widely used in IoT applications, especially in MIoT systems, where the flexibility of the form factor is critical [33]. Thus, in this paper, it is essential to investigate the impact of the proposed algorithm on the form factor of the selected EH technology. The extent of detail included in evaluated simulations could also be used to understand the requirements for the solar panel size. This is important and relevant to the topic under discussion because this study aims to develop a viable system to be implemented in a real-world scenario, such as an e-health environment. As concluded from previous scenarios, in the case of the EMR application, the rank-based algorithm had superiority over other proposed algorithms. Nevertheless, as the proposed RL-based algorithms provide the fine-tuning MAC layer adjustments, utilizing these optimal values significantly influences network performance, consequently leading to a substantial reduction in solar panel dimensions. This conclusion is also demonstrated in Figure 15, which reduces the required solar panel size to 3 cm^2. However, the smallest possible size of the panel in the scenarios with legacy, delay-based, and rank-based extremum nodes are 50 cm^2, 35 cm^2, and 20 cm^2, respectively. For instance, in the case of the legacy, the minimum size of the solar panel needs to be 50 cm^2 to keep powering the MIoT system up. Thus, legacy communications with solar panels smaller than 50 cm^2 are impossible. This comparison supported the advantage of integrating energy harvesting technologies within IoT systems.

Our previous study [35] revealed that the idle state accounts for the highest energy consumption in IEEE 802.11 nodes. This finding aligns with the fact that idle listening can be a significant source of energy drain in wireless systems. The nodes need to continuously monitor the wireless medium for available transmission slots, which consumes energy even when no actual data transmission is taking place. Therefore, longer waiting times and increased idle time would contribute to higher energy consumption by keeping the nodes in an active state for a longer duration. Based on the aforementioned discussion, it is crucial to emphasize that the remaining energy trend for legacy stations does not align with the trend observed in algorithms aimed at increasing the CW to improve the energy consumption of nodes. In other words, the energy consumption patterns of legacy stations do not follow the same trajectory as nodes implementing CW-increasing algorithms in an effort to enhance energy efficiency, and it is important to consider these findings when using the proposed algorithms.

F. DISCUSSION

As explained throughout this article, the fixed initialization of the MAC layer parameters to the default values is unsuitable and inefficient for IoT systems with unpredictable behavior. Our previous studies demonstrated that the initialization of the CW values needs to be adapted optimally to the various applications [35]. In this article, the CW value initialization is updated dynamically based on the network conditions changes to optimize the network's performance and meet the medical-grade QoS requirements. Generally speaking, the results indicated that the cell-based algorithms perform better than the node-based ones. The reason is that in cell-based algorithms, the AP considers the condition of all the associated nodes to make decisions. In contrast, in the node-wise algorithm, AP makes decisions individually for each associated node regardless of its state, compared to other nodes within the same cell. In addition, it is shown that for applications with high traffic load, the rank-based all-nodes optimization algorithm has superiority over the other proposed algorithms. This is due to the algorithm's high level of flexibility, which converges to the optimal condition very quickly. However, in the case of the low traffic load (ECG and EEG applications), the rank-based extremum nodes optimization algorithm performs better than the other algorithms.

In addition, we demonstrated that adjusting the initialization of the CW values is particularly pronounced, as it directly shapes how stations compete for channel access, consequently influencing collision rates and overall network efficiency. While AIFSN predominantly governs the hierarchy of frame priorities rather than altering the fundamental contention process, and TXOP primarily governs the sequential transmission of multiple frames after channel contention, their effects might carry a different weight than those originating from CW adjustments. Thus, it can be concluded that enhancements to AIFSN and TXOP primarily focus on optimizing and prioritizing frame transmission within an already contented channel. The actual outcomes of optimizing energy utilization, E2E delay, and PLR through RL-driven adjustments within the MAC layer are presented in Table 8. The optimal metrics corresponding to the considered medical applications, achieved via MAC parameter tuning, are distinctly highlighted. It is comprehensible that the dynamic manipulation of AIFSN and TXOP values shows the rank-based all-nodes algorithm to outperform alternative propositions for EMR applications. Conversely, the rank-based extremum nodes exhibit the most productive outcomes regarding ECG and EEG applications. Notably, despite TXOP adjustments falling slightly short of the efficiency gained through CW value optimization, it still satisfactorily fulfills the stringent medical QoS requisites, particularly concerning E2E delay.

Furthermore, we indicate that assuming the AP coordination concept in the proposed algorithms can improve the network's performance. Nevertheless, this improvement is less than the case without applying this concept. For these reasons, we declare that there is no unique initialization for CW values. In addition, introducing the sleep/wake-up mode into our proposals indicates that although the energy efficiency of the network increases, it causes an increment in the E2E delay values, while still maintaining the QoS requirements. It is noted that the most optimal value for evaluated metrics in each set of simulations is highlighted in Table 7 and Table 8, where the assessed PLR values for ECG and EEG applications are negligible. We have demonstrated that the acquired optimal MAC layer parameters yield a discernible enhancement in network performance, with a particular focus on energy consumption. This improvement surpasses the impact of isolated adjustments to individual MAC layer parameters. In the end, we convey that deploying the proposed RL-based optimization algorithms align with fine-tuning of MAC layer parameters making the panel size reduction in IoT systems possible; thus, it takes a crucial step towards achieving sustainability in future IoT systems.

VII. CONCLUSION AND FUTURE WORK

This article presented the possibility of integrating energy harvesting technologies within a Wi-Fi-based MIoT system through extensive simulations on the ns3-gym framework. We proposed three RL-based algorithms for the IEEE 802.11 MAC layer optimization, a novel approach that improves the energy efficiency of the system while provisioning the medical grade QoS requirement. The obtained results demonstrated that in the case of applications with high traffic load, the rank-based all-nodes algorithm can reduce the energy consumption of the system by more than 25%. We also demonstrated that further improvement could be achieved by deploying the sleep/wake-up method to the proposed algorithm, in which the improvement increased to 30%. In addition, the AP coordination concept from the upcoming IEEE 802.11bn amendment was evaluated in this system. We believe this article will shed light on integrating energy harvesting into dense networks such as IoT systems. Moreover, our research highlights that the acquired optimal MAC layer parameters bring about a noticeable enhancement in network performance, particularly regarding energy consumption. This advancement goes beyond the effects achieved by making isolated adjustments to individual MAC layer parameters. The enhancements introduced by the proposed algorithm and the particular fine-tuning of MAC layer parameters demonstrate the feasibility of downsizing solar cells while enhancing their flexibility for integrating this EH technique with IoT devices. These advancements pave the way for integrating them seamlessly into IoT devices, particularly wearable medical devices, leading to a new era of compact, versatile, and energy-efficient technology. This research can be enhanced by introducing a deep learning approach to the proposed algorithms to make the decisions more accurate and flexible to the network changes. Furthermore, we can consider more information (other MAC layer parameters) and different medical grades QoS requirements for the RL-based optimization algorithm.

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6

Summary of Findings, Discussion, and Directions for Future Research

The evolution of the IoT paradigm's future development indicates a remarkable escalation in IoT devices, exerting profound influence across diverse sectors, including industry, agriculture, healthcare, and more. Among the key considerations, ensuring energy efficiency in IoT systems stands prominent, a challenge that finds its solution in the advent of sustainable IoT systems. Instead of conventional batteries, passive technologies such as EH techniques are deployed in these systems. By adopting such approaches, not only is the burden of maintenance cost alleviated, but also the adverse environmental impacts are mitigated, concurrently enhancing the operational lifespan of IoT devices.

Nonetheless, the challenge of managing energy within the IoT paradigm extends beyond the disposal of conventional batteries. Another critical aspect of energy consumption in the IoT paradigm is associated with the wireless communication infrastructure that is deployed in these systems. The prevalent method of communication for most IoT devices relies on wireless technologies, where the IEEE 802.11, commonly known as Wi-Fi, dominates indoor IoT environments. However, due to its MAC layer operations, Wi-Fi emerges as an energy-intensive technology, thus raising concerns about its environmental impact. The emissions of significant CO_2 into the atmosphere from battery waste, and the implicit energy needs from communication technologies like Wi-Fi can expedite global warming, amplifying its urgency. As deploying dense or intricate networks like heterogeneous networks increases these concerns, the path towards a sustainable IoT future entails integrating EH techniques. Such integration becomes imperative to shorten the environmental repercussions, which requires a reduction in the energy consumption of the deployed wireless communication technologies in the system.

While the IEEE 802.11 working group has been introducing various features into amendments to mitigate network energy consumption, there remain opportunities for enhancement. These encompasses enhancing the scheduling of the MAC layer, simplifying operational intricacies within nodes, and introducing coordinated transmission mechanisms to the inherently distributed framework of Wi-Fi communication while ensuring seamless backward compatibility.

In this Ph.D. study, our objective revolves around exploring the viability of incorporating passive technologies, specifically EH techniques, to enhance the energy efficiency of IoT systems. Within this framework, we have clarified that optimization possibilities exist within the operations of the MAC layer of IEEE 802.11, which can effectively mitigate the total energy consumption of the network and render it manageable for the integration of EH technology within IoT systems.

Furthermore, we have undertaken an evaluation of the utility of ML methods within the examined scenario. This evaluation underscores the significance of ML techniques in the context of Wi-Fi 7 and Beyond, showcasing their relevance and importance.

This chapter first summarizes the key findings, followed by a discussion of limitations. It concludes by outlining potential directions for future research.

6.1 Summary of Findings and Discussion

Throughout this Ph.D. study, we have substantiated that existing EH technologies need to provide continuous power for IoT devices reliant on various wireless communication technologies. Achieving a seamless integration, necessitates optimizing energy consumption within the IoT layers, particularly concerning the diverse wireless communication technologies. Consequently, focusing on the MAC layer operations, which notably deplete the energy budget of wireless communication, emerges as a key approach for implementing energy optimization techniques and preserving valuable energy resources.

In our initial contribution supporting this argument, we conducted a comprehensive review of MAC layer operations and various MAC optimization techniques, several of which find application in current IoT wireless communication technologies. Building upon the insights gained from this examination of MAC layer operations, we developed a unified analytical approach to systematically assess energy models for each technology. Additionally, we extensively examined the available EH technologies and considered their limitations. Our analysis led us to assert that LPWAN technologies are well-suited for diverse IoT use cases, owing to attributes such as duty-cycle regulation, simple random access mechanisms, low energy consumption, and long-range communications. Aligned with LPWAN technologies, since IEEE 802.11ah explicitly designed for IoT systems, it meets crucial requirements such as long-range capabilities, low power consumption, and higher data rates.

Our investigation into EH technologies confirmed that devices like photovoltaic panels or thermocouples are viable for integrating LPWAN, IEEE 802.11ah, and upcoming amendments (Wi-Fi 7 and Beyond) wireless communication technologies. Hence, we identify LPWAN and IEEE 802.11ah as promising wireless technologies within IoT systems. This work also elaborates on how existing EH MAC protocols adapt to integrating EH in IoT systems, precisely comparing these MAC protocols based on EH-related network parameters. Our analysis revealed that only 23% of the reviewed literature considered the ENO condition, a crucial parameter for enabling EH in IoT systems.

Moreover, we demonstrated that the hybrid access MAC protocols exhibit significant potential for IoT systems equipped with energy harvesters, showcasing high adaptability to node energy levels and effectively reducing network energy consumption in 48% of the literature analyzed. Alongside these hybrid access energy harvesting MAC protocols, cross-layer mechanisms have demonstrated noteworthy energy consumption reductions within the network. However, their application still needs to be improved due to the substantial computational complexity they entail, warranting further development and maturation in current technologies. These findings are explained in Chapter 3 in detail.

The outcomes of the second contribution (see Chapter 4) underscore the need to customize the CW selection of the EDCA mechanism to conform to various medical applications. For example, within this study, we observed diverse traffic characteristics among the considered medical applications (ECG, EEG, and EMR). As a result, a universal and optimal CW combination applicable across all ACs does not exist. Instead, each application necessitates a distinct CW combination within its respective AC.

Furthermore, our findings demonstrate that network performance, specifically in terms of medical-grade QoS metrics like E2E Delay and PLR, can be enhanced by implementing AP coordination as outlined in the upcoming IEEE 802.11be amendment (varies with applications and metrics). To achieve this, the transmission in slave cells is intentionally delayed by adjusting their CW values. Subsequently, the CW values are reduced in master cells to afford them more opportunities for initiating transmissions. Modifying the right balance in CW values for both master and slave cells is critical to avoid increasing the collision rates due to excessively low CW values, or excessively delay slave cells if CW is set to a large value.

Additionally, the proposed algorithm, synchronized with the sleep/wake-up method, results in reduction in the network's energy consumption while ensuring that QoS metrics remain within acceptable thresholds. Lastly, we emphasize the significance of EH within the system and highlight the effectiveness of our proposed algorithm in drastically reducing the solar panel dimension required to 7 cm^2.

In the third contribution (see Chapter 5), we highlighted the inadequacy and inefficiency of the fixed initialization of MAC layer parameters to standard default values in IoT systems with unpredictable behavior. Consequently, within this contribution, we proposed a dynamic update for initializing the CW values based on changes in network conditions, aiming to optimize the network's performance and meet the stringent medical-grade QoS requirements.

The results show outstanding performance of cell-based algorithms compared to node-based ones. In cell-based algorithms, the AP considers the conditions of all associated nodes when making decisions. Conversely, node-wise algorithms have the AP making decisions for each associated node individually, regardless of its state relative to other nodes within the same cell.

Additionally, we demonstrated that the *rank-based all-nodes* optimization algorithm outperforms other proposed algorithms for applications with high traffic loads. This superiority arises from the high flexibility of the algorithm, allowing it to converge to optimal conditions rapidly. Conversely, for low-traffic load applications (such as ECG and EEG), the rank-based extremum nodes optimization algorithm performs better than other algorithms.

Furthermore, we illustrated the significance of adjusting the initialization of CW values as it directly impacts how stations contend for channel access, thereby influencing collision rates and overall network efficiency. While AIFSN primarily governs frame priority hierarchy and TXOP regulates sequential frame transmission after channel contention, their effects may carry different weights compared to adjustments in CW values. Hence, optimizing AIFSN and TXOP focuses on enhancing and prioritizing frame transmission within a contended channel. Dynamic manipulation of AIFSN and TXOP values revealed that the rank-based all-nodes algorithm outperforms other propositions for EMR applications. In contrast, rank-based extremum nodes present optimal outcomes for ECG and EEG applications. Despite slightly falling short of CW value optimization in efficiency, TXOP adjustments satisfactorily meet stringent medical QoS requisites, particularly concerning E2E delay.

Additionally, we underscored that assuming the AP coordination concept in the proposed algorithms could enhance network performance, though to a lesser extent than without this concept. The results demonstrated that the rank-based all-nodes algorithm can reduce the system's energy consumption by over 25% for applications with high traffic loads. Moreover, integrating the sleep/wake-up mode into our proposals indicated a 30% increase in network energy efficiency, albeit at the expense of slightly higher E2E delay values, while still adhering to QoS requirements.

We further explained that deploying the sleep/wake-up method in the proposed algorithm can lead to additional improvements. The obtained optimal MAC layer parameters significantly enhance network performance, particularly in energy consumption, surpassing the impact of individual MAC layer parameter adjustments. In conclusion, deploying the proposed RL-based optimization algorithms, aligned with MAC layer parameter fine-tuning, is critical in reducing panel size (down to 3 cm^2) in IoT systems. This marks a crucial stride toward achieving sustainability in future IoT systems.

6.2 Future Works

Finally, this study provides comprehensive guidance for unresolved issues and challenging research topics regarding sustainability in the IoT paradigm, specifically from MAC layer protocols incorporating EH techniques perspective. These research lines can be divided into the following points.

6.2.1 Integrating Advanced ML Approaches within Wireless Communication Technologies

Incorporating advanced ML techniques, such as DRL, into the envisioned optimization framework provides a sophisticated way of predicting complex functions. Within these techniques, the complexities of the optimization problem can be effectively addressed, enabling dynamic fine-tuning of a diverse range of MAC and physical layer parameters. This integration empowers the system to adapt seamlessly to the network's dynamic conditions in real-time, optimizing performance during each operational window without degrading the functionality of other network processes. As an example, through the utilization of DRL, the proposed approach controls the learning capabilities of the system, allowing it to adjust and refine MAC layer parameters autonomously based on evolving environmental factors. This not only enhances the adaptability of the network but also contributes to the overall efficiency and responsiveness of the system, aligning it more closely with the dynamic demands of future wireless communication environments.

While integrating ML approaches in the upcoming generation of cellular networks and Wi-Fi has garnered considerable interest, there remains a substantial opportunity for further enhancements in network performance while concurrently preserving energy efficiency and moving towards sustainability.

6.2.2 Enhancing the Collective Optimization of Wi-Fi Features

Maximizing the potential of Wi-Fi's collective features presents a compelling opportunity for enhanced performance. In such a context, a central controller is critical in orchestrating the fine-tuning of MAC layer parameters. This strategic management encompasses a subtle consideration of dynamic shifts occurring in the physical layer, ranging from data rate variations to antenna orientation alterations. According to the dynamic changes of the network parameters, the controller can optimize the overall efficiency of the Wi-Fi network, ensuring seamless adaptability to changing conditions. This proactive approach enhances the network's stability and contributes to a more reliable and responsive wireless communication environment. As we delve into the intricacies of Wi-Fi optimization, integrating intelligent control mechanisms becomes instrumental in developing this ubiquitous technology's full spectrum of capabilities. Therefore, defining and developing orchestrators at the MAC layer is challenging and requires more effort.

It is worth mentioning that in the next generation of cellular networks, orchestrators play a critical role in coordinating and managing various components to ensure the efficient operation and optimization of the network, such as resource allocation, network slicing, load balancing, interference management, and energy efficiency.

6.2.3 Overseeing and Managing Novel and Adaptable yet Complex Features of the Next Generation Wi-Fi

Wi-Fi 7 and Beyond indicate a new era in wireless communication, introducing advanced capabilities to meet the evolving demands of the future. As anticipated in upcoming IEEE 802.11 updates, several innovative capabilities will enter the Wi-Fi standard. Among these developments that stand out are multi-link operation and the potential addition of multi-AP coordination, which will smoothly enhance the current feature set.

This next wave of Wi-Fi technology builds upon existing features and tries to enhance them, such as OFDMA, downlink and uplink MU-MIMO, spatial reuse mechanisms, and channel aggregation. Collectively, these features contribute to optimizing network efficiency, enhancing data throughput, and reinforcing the overall performance of Wi-Fi networks. This adaptability will help to revolutionize the management of diverse real-time data streams, enabling more efficient utilization of available resources. However, these new features may increase the network's energy consumption, which may require deploying the power-saving mode techniques in the next generation Wi-Fi.

6.2.4 Simultaneous Operation and Collaboration Between Wi-Fi and 5G and Beyond

Throughout this Ph.D. study, our focus has predominantly centered on a Wi-Fi scenario. However, in IoT applications, particularly in the context of smart cities, devices often operate on diverse technologies and protocols, each characterized by distinct constraints. One of the paramount challenges encountered in heterogeneous networks (HetNets) lies in the coexistence of these varied technologies. The inherent heterogeneity introduces complexities in network structure, leading to increased energy waste primarily due to interference and a lack of efficient resource management. In HetNets, the complicated interplay between different devices exacerbates energy inefficiencies. Given the heterogeneous nature of HetNet devices, energy efficiency becomes a critical consideration for fostering profitability and sustainability. Consequently, implementing energy-saving strategies and effective power consumption management emerges as imperative in establishing robust and enduring networks.

Notably, exploring green heterogeneous networking has been the subject of considerable research. Some studies delve into dynamic optimization at the MAC layer, exemplified by NOMA, as a means to mitigate energy consumption. Additionally, the concept of defining a universal ENO value for the entire network has been proposed. Despite these efforts, addressing the multifaceted challenges presented by the heterogeneous nature of HetNet devices remains an ongoing and intricate research direction, which intensifies in the case of dense HetNet configuration.

6.2.5 Provisioning Green Connectivity in the Next Generation of the Wireless Communication Technologies

Information and communication technologies (ICT) that incorporate EH technologies positively affect sustainability and decrease CO_2 footprint while ensuring clean and affordable energy. Next-generation technologies such as 6G and Wi-Fi8 are among the wireless communication technologies that consider EH integration a critical enabling factor and are able to promote global sustainability.

Extremely-Enhanced Mobile Broadband (eMBB), Extremely-Reliable and Low-Latency Communication (URLLC), Extremely-Massive Machine-Type Communications (mMTC), and Extremely-High Energy Efficient (EHEE) communication are the theoretical directions that 6G communication is moving towards. Furthermore, 6G aims to replace millimeter-wave bands, which offer high-speed communication at a significant energy cost. Furthermore, significant interference affect the mix of terrestrial and satellite communications in 6G communication, increasing the network's energy usage. To overcome these constraints and challenges, 6G connection proposes technologies like Backscatter Communication (BsC) and wireless power transfer (energy beamforming). In the former scenario, the wireless nodes will passively receive radio signals from the surrounding environment, enabling battery-free operation; in the latter scenario, a collection of high beam antennas is concentrated on transferring the energy through narrow beams to a particular set of nodes.

The next-generation Wi-Fi introduces advanced features such as multi-AP coordination, distributed multi-link operation, and MAC and PHY layer enhancements. While these advancements may lead to increased energy consumption within the network, the upcoming amendment brings potential benefits through passive Wi-Fi. This innovative approach leverages energy-efficient backscatter communication to reduce the system's overall energy consumption significantly. Another notable technique contributing to energy reduction and sustainability in the next generation of Wi-Fi is the AP power-saving method. This approach prioritizes efficiency by deactivating the AP interface during prolonged periods of inactivity. The AP becomes functional and active only when a frame is ready for transmission. This dynamic strategy optimizes energy usage and aligns with providing a sustainable and resource-efficient Wi-Fi ecosystem. In this PhD study, this feature was deployed and evaluated. The evaluations demonstrated that a considerable amount of energy can be conserved through this method. However, the power-saving mechanisms for the upcoming amendment are still in their early stage and require more research and investigation.

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List of Publications

Journal Papers

- Famitafreshi, G., Afaqui, M.S., Melià-Seguí, J. *"A Comprehensive Review on Energy Harvesting Integration in IoT Systems from MAC Layer Perspective: Challenges and Opportunities".* Sensors **2021**, 21, 3097, doi: org/10.3390/s21093097

This paper is published in the Sensors journal by MDPI with a (Q_2) index according to the Journal Citation Reports (JCR), has obtained over 15 citations as of December 2023.

- Famitafreshi, G., Afaqui, M.S., Melià-Seguí, J. *"Enabling Energy Harvesting-Based Wi-Fi System for an e-Health Application: A MAC Layer Perspective".* Sensors **2022**, 22, 3831. 1, doi: org/10.3390/s22103831

This paper is published in the Sensors journal by MDPI with a (Q_2) index according to the Journal Citation Reports (JCR), has obtained 3 citations as of December 2023.

- G. Famitafreshi, M. S. Afaqui and J. Melià-Seguí, "Introducing Reinforcement Learning in the Wi-Fi MAC Layer to Support Sustainable Communications in e-Health Scenarios," in IEEE Access, vol. 11, pp. 126705-126723, **2023**, doi: 10.1109/ACCESS.2023.3331950.

This paper is published in the IEEE Access journal with an impact factor of 3.47 (Q_1).

Other publications

- Garrido, L.A., Dalgkitsis, A., Famitafreshi, G., Siokis, A., Ramantas, K. and Verikoukis, C., 2023, December. An Experimental Platform of a Beyond-5G Network with Machine Learning Integration. In GLOBECOM **2023-2023** IEEE Global Communications Conference (pp. 62-67). IEEE.

This paper is published in the IEEE Global Communications Conference.

- Famitafreshi, G., and Cano, C. “Achieving proportional fairness in WiFi networks via bandit convex optimization”. Annals of Telecommunications, **2022**, 77(5-6), 281-295.

This paper, is published in the Annals of Telecommunication journal with a (Q_2) JCR index.

List of Projects

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- RF-VOLUTION: Spanish Ministry of Science, Innovation and Universities (PID2021-122247OB-I00)
- HydraSport: Spanish Ministry of Culture and Sports, and the European Funds for the Recovery, Transformation and Resilience Plan (EXP_75087)
- SPOTS: Spanish State Research Agency-Spanish Ministry of Science, Innovation, and Universities (RTI2018-095438-A-I00)
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- PoC eHealth Center: Universitat Oberta de Catalunya (RH404)