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Review

Green IoT: A Review and Future Research Directions

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Abstract: The internet of things (IoT) has a significant economic and environmental impact owing to the billions or trillions of interconnected devices that use various types of sensors to communicate through the internet. It is well recognized that each sensor requires a small amount of energy to function; but, with billions of sensors, energy consumption can be significant. Therefore, it is crucial to focus on developing energy-efficient IoT technology and sustainable solutions. The contribution of this article is to support the implementation of eco-friendly IoT solutions by presenting a thorough examination of energy-efficient practices and strategies for IoT to assist in the advancement of sustainable and energy-efficient IoT technologies in the future. Four framework principles for achieving this are discussed, including (i) energy-efficient machine-to-machine (M2M) communications, (ii) energy-efficient and eco-sustainable wireless sensor networks (WSN), (iii) energy-efficient radio-frequency identification (RFID), and (iv) energy-efficient microcontroller units and integrated circuits (IC). This review aims to contribute to the next-generation implementation of eco-sustainable and energy-efficient IoT technologies.

Keywords: internet of things; green IoT; energy-efficient; energy harvesting; wireless charging; green 6G; green communications; eco-sustainable WSN; RFID; M2M

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1. Introduction

1.1. Background and Motivations

The internet of things (IoT) is a revolutionary technology driving telecommunications advancements and improving people's quality of life worldwide. The IoT also has the potential to boost the global economy significantly. It is anticipated that the global economic impact of the IoT will be between USD 2.7 trillion and 6.2 trillion by 2025 [1] due to IoT devices that are a critical component of emerging applications and play a central role in the widespread adoption of machine type communications, as shown in Figure 1 [2]. According to experts, the IoT has the potential to revolutionize different smart zones including modern healthcare applications, smart homes and smart cities [3]. In particular, the healthcare industry is expected to see annual global economic growth of between USD 1.1 trillion and 2.5 trillion by 2025 [4] due to IoT technology.

As the IoT continues to expand, telecom operators should strive to enable the technology with fewer challenges. Currently, there are more internet-enabled objects than people on Earth, and this number is envisioned to continue growing in the near future [5]. It is reported that 45% of all internet traffic will be machine-to-machine (M2M) traffic by 2024, thanks to the IoT's ability to allow physical objects to communicate among themselves and perform tasks with zero human intervention. This is achieved through the use of various types of smart sensors, such as RFID and actuators, which work together in order to transmit information collected from their surroundings to the internet using sensing technology [1]. The IoT enables the network objects to perform tasks by coordinating decisions and sharing information through these sensors.

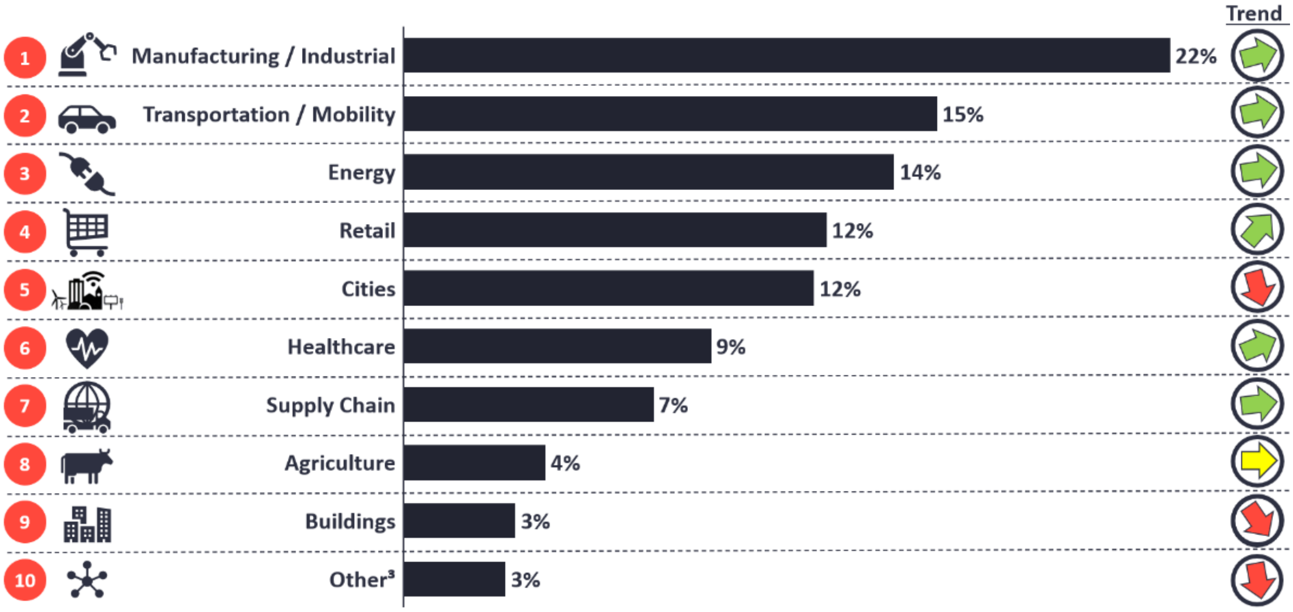

Figure 1. Top 10 IoT application areas in 2020.

According to [6], each active RF identification device requires a small quantity of electrical power to function. However, when billions of such network devices are connected that are consuming energy on a daily basis, and a significant number of data points transmitted by sensors need to be processed by large data centers, it becomes necessary to have significant processing and analytics capabilities [7,8], which can be energy-intensive. Therefore, the energy consumption in large-scale IoT systems should be carefully considered. To address these energy concerns, a new field of research known as "green IoT" has emerged. This initiative aims to elevate energy efficiency and reduce CO_2 emissions for IoT technology [9]. It is clear now that the IoT will have a considerable economic and environmental impact in the forthcoming years. As a result, there is a pressing need to research and develop advanced techniques and strategies to address the energy needs of billions of devices. As traditional energy sources become scarce and energy consumption continues to increase, the idea of green IoT (GIoT) has gained significance for researchers and vendors alike. The concept of green IoT is crucial for finding new ways to downsize energy consumption and increase eco-sustainability.

The objective of the GIoT initiative is to enhance energy efficiency throughout IoT systems. It aims to make every aspect of the IoT more energy-efficient, from the design phase to implementation [10]. This has sparked research in both academia and industry to come up with various methods to escalate energy efficiency in IoT. As a result, the research in the context of green IoT encompasses a wide range of challenges and mitigation techniques. However, research on GIoT techniques can be divided into two main categories [11]: (i) software, which aims to reduce energy waste through more efficient resource utilization, and (ii) hardware, which envisions improving energy efficiency in IoT devices. This latter category is the focus of our study.

1.2. Related Works and Contributions

There has been an increase in the number of survey papers on green IoT that have garnered attention in recent times [2,10,12–15]. Reference [12] conducted an analysis of different approaches for achieving green IoT; however, they did not consider the use of specific green IoT models in their analysis. Reference [13] examined energy consumption under several cloud deployment scenarios, but their models did not take into account Quality of Service (QoS) metrics in some certain scenarios. Reference [14] conducted a thorough analysis of energy harvesting in wireless sensor networks (WSNs) using distinctive environmental sources. However, using a different storage medium for the harvested energy than the device itself may incur an energy loss, which would require additional effort to address. Reference [15] suggested that implementing energy-efficient measures in heating, air conditioning and ventilating systems would result in a significant amount of energy savings. Despite significant research in the field of GIoT, energy conservation schemes have yet to be thoroughly investigated. Reference [2] conducted a comprehensive analysis of green IoT techniques and proposed five principles for the GIoT. Additionally, the authors emphasized the use of case studies, specifically citing smart phones as an example, as a valuable tool for understanding IoT. However, the aforementioned studies were somewhat lacking in their depth of explanation. In the rapidly evolving field of green IoT, it is important to highlight new developments and provide clear insights to researchers in order to enable them to settle on the best solutions that promote eco-sustainability with attention to green IoT.

This review paper differs from other reviews on green IoT in its goal to provide an extensive overview of the recent state-of-the-art energy-saving strategies and practices in the context of green IoT, specifically focusing on the energy efficiency of green hardware IoT devices. In order to achieve that goal, this study attempted to cover as many relevant topics as possible within the scope of the paper. However, due to size limitations, the focus was on in-depth analysis of particularly controversial or important sub-areas within the larger domain of green IoT in order to arrive at precise, concrete, and concise conclusions. This study covers the following sub-domains within the field of green IoT: (i) energy-efficient M2M communications, (ii) energy-efficient and eco-sustainable WSN, (iii) energy-efficient RFID, and (iv) energy-efficient integrated circuits and microcontroller units. M2M communication is a foundational aspect of IoT and sensor networking and serves as a crucial element in current systems, along with RFID technology. However, both the sensor networking and RFID technology will undergo thorough examination in this study, because they are considered key components in the field of green IoT. The main contributions of this paper are outlined as follows:

- A review of current research on the green IoT ecosystem, including recent industry developments and embedded systems, key areas of application, deployment, challenges, and key players focusing on RFID, WSN, processors, MCUs, and ICs.
- A discussion of key design choices and features for RFID and WSNs that are considered to be among the highest priorities within green IoT networks.
- An exploration of the limitations and challenges that need to be overcome to fully realize the potential of a green IoT, including issues related to interoperability, security, and privacy, and recommendations for future research to support the efforts in developing hardware for green IoT that promotes eco-sustainability.

1.3. Paper Organization

The structure of this study is as follows: Section 2 presents the research methodology of the article. Section 3 provides an overview of the four (4) green hardware IoT frameworks that are considered in this study. In Section 4, energy-efficient solutions for M2M communication are discussed. Section 5 presents a detailed analysis of energy-efficient and eco-sustainable WSNs. Section 6 discusses energy-efficient RFID. The topic of energy-efficient MCUs, ICs, and processors is covered in Section 7. Potential future research directions are outlined in Section 8. Finally, Section 9 concludes the paper, summarizing key insights.

2. Methodology

To write this literature review on energy-efficient and eco-sustainable strategies for future massive green IoT networks, a systematic process was used to gather information. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method was used to formulate the research questions (RQ) that guided the study.

- ***RQ1:*** What are the energy-efficient techniques that can be used to implement massive green IoT networks?

This question aims to identify the various energy-efficient techniques mentioned in the literature, evaluate their advantages, and examine their trends to aid the implementation of massive green IoT networks.

- ***RQ2:*** How can energy consumption be reduced in IoT devices without compromising performance and functionality?

The objective of this question is to explore the integration of various software and hardware techniques and approaches to minimize energy wastage caused by inefficient resource utilization.

- ***RQ3:*** What are the key challenges in designing and implementing green IoT networks?

This question aims to investigate the symmetry between energy efficiency and key performance indicators, such as coverage and signal strength, in IoT networks.

After identifying the research questions, the following keywords were established to create the research string (RS): “Green IoT”, “Energy efficiency”, “Green communications”, “Energy harvesting”, and “Low-power design”. The research string (RS) is indicated as:

RS = (Green communications OR Green IoT) AND (GIoT OR Energy harvesting OR Energy efficiency OR IoT)
AND (Low-power design OR low-power devices)

After constructing the RS, we started with the document search phase. The databases that were consulted for this study included Science Direct, IEEE, Scopus, Springer, Web of Science, Wiley Online Library, Association of Computing Machinery (ACM) and MDPI. These databases were chosen due to their wide range of publications and previous research. An effort was made to include all databases that have been used by authors in prior studies. Notably, no additional techniques were applied to expand the results, as the number of articles obtained from the aforementioned databases was sufficient. We implemented a three-stage process, as demonstrated in Figure 2.

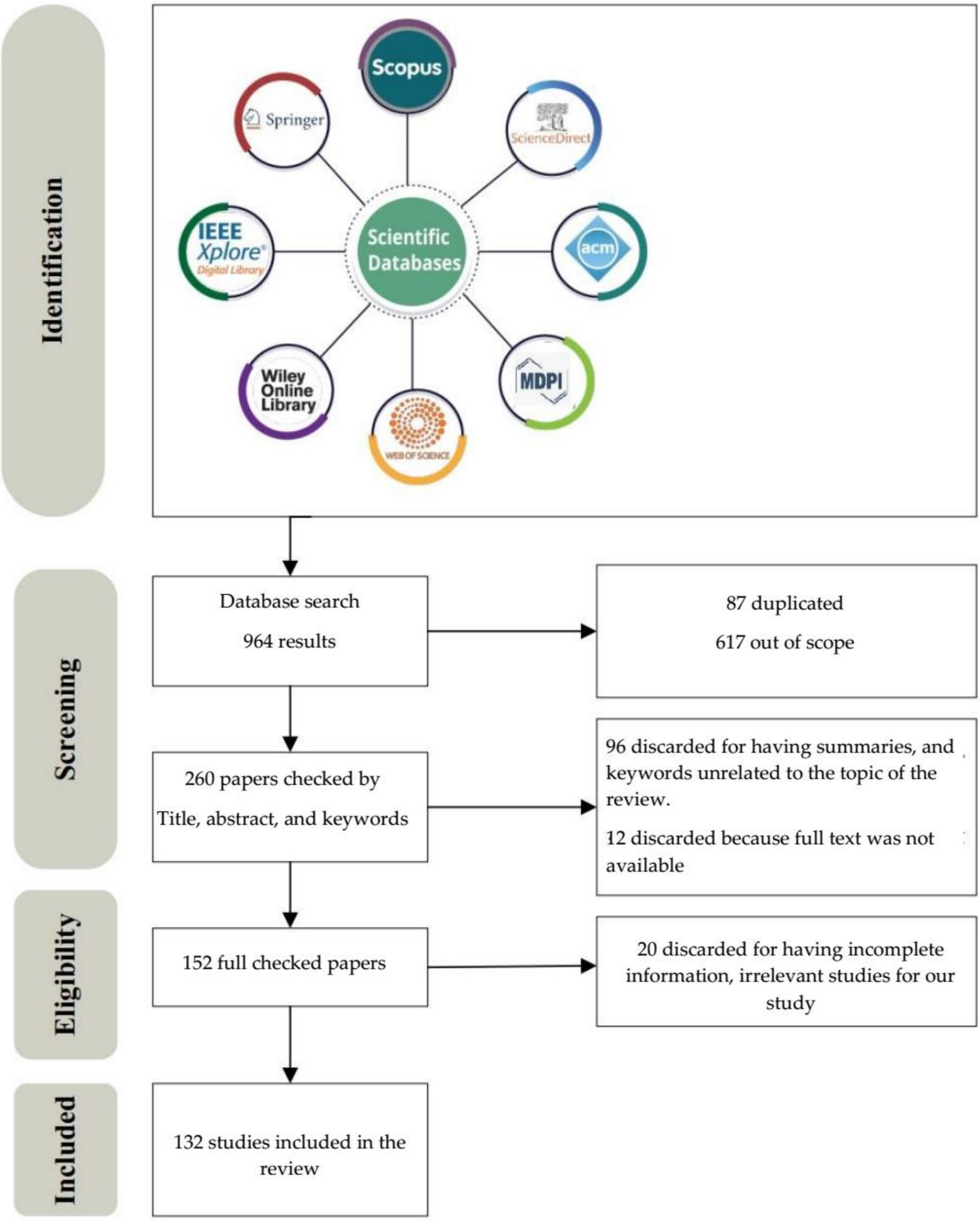

Figure 2. Research methodology of the article.

3. Green Hardware IoT Framework

This section represents a brief overview of the four (4) green hardware IoT frameworks and includes a summary of proposed energy-saving technology classifications in Figure 3. The following sections cover more detailed information on these topics.

- **Machine-to-Machine (M2M):** M2M technology refers to the ability of smart devices to communicate with each other and exchange data without the need for human intervention. It forms the basis of IoT and allows for the creation of smart systems that can operate and make decisions independently [16]. One of the key applications of M2M technology is in the field of smart cities [11], where it can be used to optimize the performance of infrastructure such as traffic systems, public transportation, and utilities. M2M communication can also be utilized in industrial settings to improve efficiency and productivity, as well as in healthcare to enable remote monitoring and treatment of patients. In order to achieve energy efficiency in M2M systems, various strategies can be employed (as shown in Figure 3). These may include the use of low-power communication protocols, the implementation of energy-efficient protocols for data transmission, and energy-harvesting techniques to power M2M devices. Overall, M2M technology plays a crucial role in the advancement of the IoT and has the potential to substantially improve the efficiency and sustainability of a wide range of systems.
- **Wireless Sensor Networks (WSNs):** WSNs are networks of small, energy–efficient devices equipped with sensors that are capable of wirelessly communicating with each other and with a central hub. WSNs can be used to monitor and collect data from various environments and are commonly deployed in a broad range of applications, including industrial monitoring, healthcare, and environmental monitoring. In order to make WSNs more energy-efficient, various strategies can be employed. These may include the use of energy-efficient communication protocols, the implementation of energy-harvesting techniques to power the sensors, and the use of energy-efficient storage and data processing methods (as depicted in Figure 3). One promising research context in the field of WSNs is the use of machine learning algorithms to improve energy efficiency. These algorithms can be applied to streamline data transmission and lower the overall network energy usage. Overall, WSNs have the potential to greatly boost efficiency and sustainability and will likely continue to be an important area of research in the field of IoT [17].
- **Radio-Frequency Identification (RFID):** RFID is a wireless technology that identifies and tracks objects using radio waves. It consists of a small chip, known as an RFID tag, which is associated with an object and a reader that is able to detect and communicate with the tag. RFID technology has a wide range of applications, including inventory tracking, supply chain management, and asset management. The technologies for improving energy efficiency may include the use of low-power communication protocols, the implementation of energy-efficient data processing techniques, and the use of energy-harvesting methods to power RFID devices. One promising area of research in the field of RFID is the development of passive RFID tags, which do not require an energy source and can operate indefinitely as long as they are within range of an RFID reader [18].
- **Microcontroller Units (MCUs) and Integrated Circuits (ICs):** MCUs and ICs are key components of many electronic devices, including those used in the IoT. MCUs are small computers that are used to control and monitor the operation of a device, while ICs are electronic circuits that are used to process and transmit information. The strategies for enhancing the energy efficiency of MCUs and ICs may include the use of low-power design techniques, the implementation of energy-efficient data processing algorithms, and the incorporation of energy-harvesting methods to power the devices. One promising area of research in the field of MCUs and ICs is the use of ML algorithms to optimize their performance and reduce energy consumption [19]. Another area of

focus is the emergence of more energy-efficient materials and intelligent manufacturing processes for these devices.

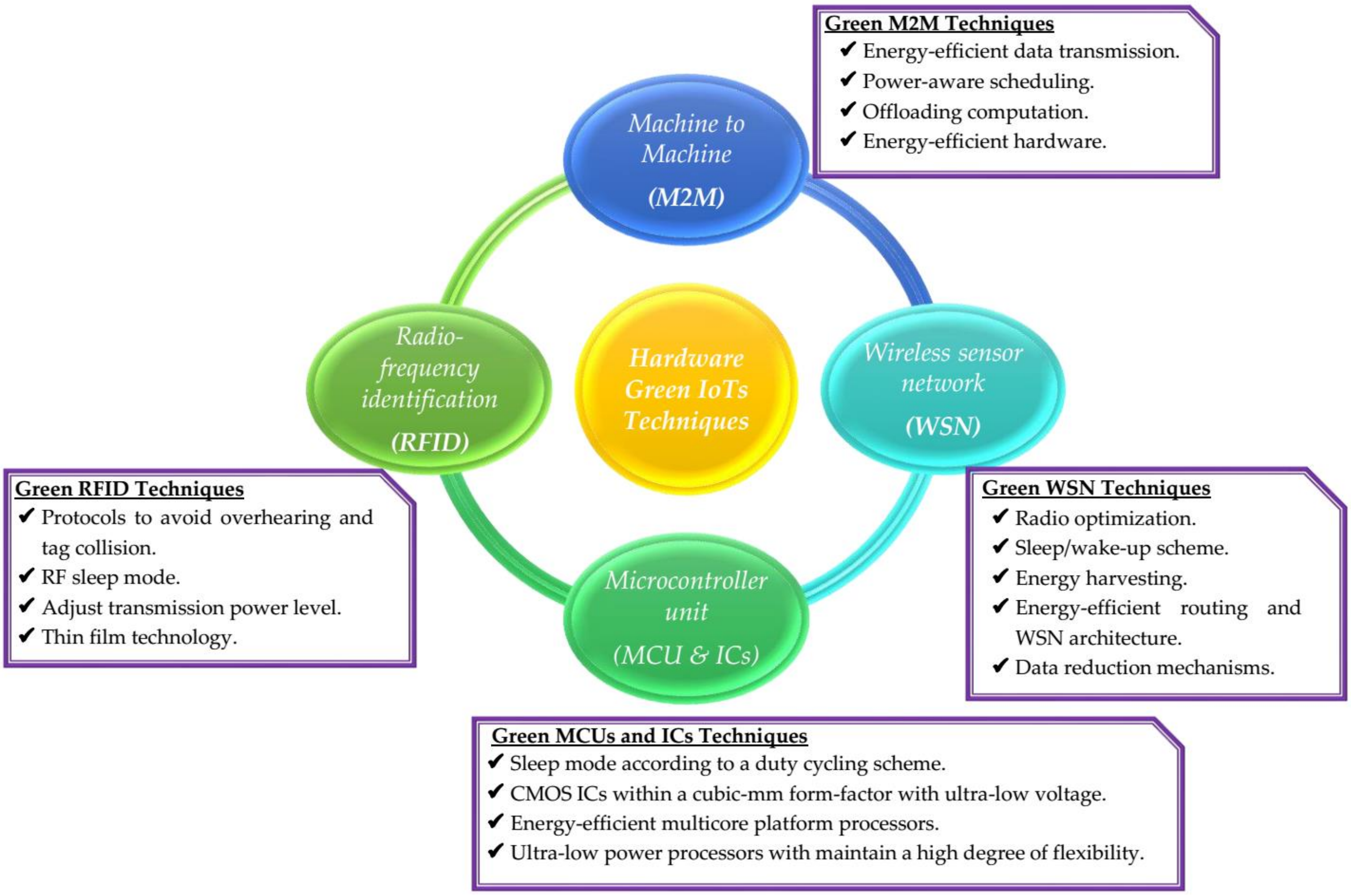

Figure 3. The proposed framework and energy-efficient technologies for IoT in this study.

4. Energy-Efficient M2M Communications

M2M communication involves the exchange of data between devices or sensors without the need for human intervention [16], and these devices often have limited energy resources due to their small size and/or reliance on batteries [11]. Techniques that can help M2M communication systems use less energy are, therefore, inevitable. As a result, techniques that can reduce the energy consumption of M2M communication systems are of significant interest. The proposed methods for enhancing the energy efficiency of M2M in the IoT environment are outlined in Figure 4. The amount of energy saved for each approach/technique relies on a number of key factors, including the specific technique being used, the type of M2M communication system, the device hardware and software, and the operating environment. Thus, it is difficult to accurately quantify the amount of energy that can be saved through the use of various techniques for energy-efficient M2M communication. A detailed discussion of the potential approaches to improving the EE of M2M is given in the following subsections.

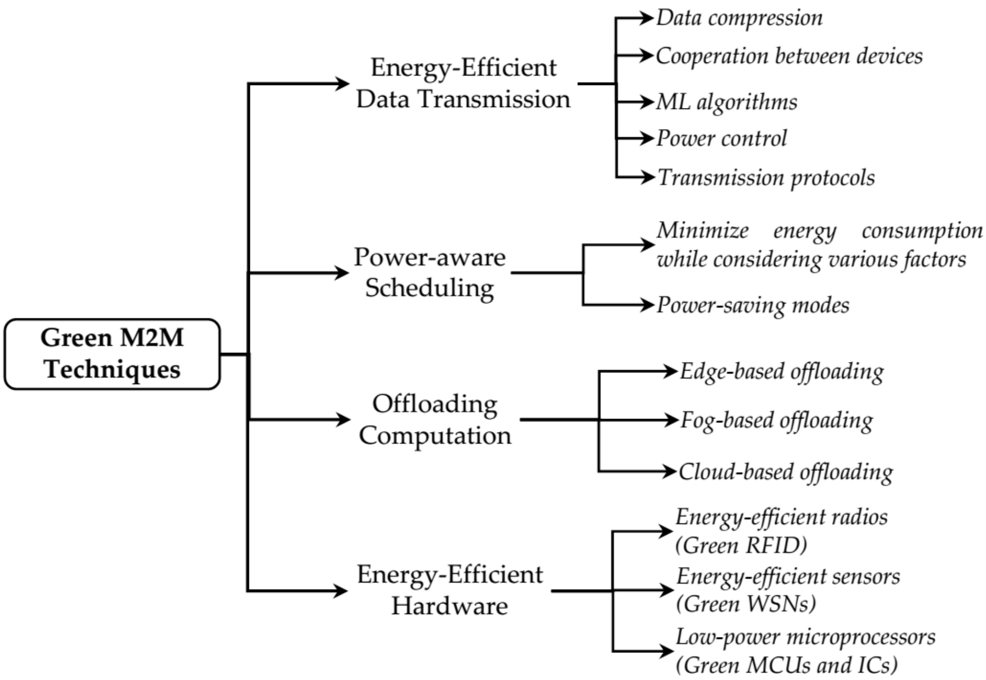

Figure 4. Classification of energy-efficient techniques for M2M communications.

4.1. Energy-Efficient Data Transmission

The approaches to improving the energy efficiency of M2M data transmission that are listed in the literature can be summarized as follows:

(i) *Data compression*: Compressing data before transmission can reduce the amount of energy used to transmit it. Data compression techniques that are straightforward to use and have low computational requirements often use less energy [20]. However, the balance between the amount of data that is compressed and the energy needed can be complex, as techniques that compress data more may require more energy [21]. Table 1 provides a summary of data compression techniques, highlighting their respective advantages and disadvantages. Based on information from existing reviews or research in the field [22–24], these factors were determined by the authors of this article.

(ii) *Cooperation between devices*: M2M devices can collaborate in the transmission of data and share resources such as power, bandwidth, and processing capabilities to lower energy consumption and enhance system performance [25–30].

(iii) *ML algorithms*: ML algorithms can be used to minimize data redundancy and optimize the rate of data transmission in multicell networks. The type of algorithm depends on the specific needs of the M2M application, including the amount and complexity of available data and the required accuracy. Testing different algorithms and evaluating their performance can help determine the most suitable one for a specific M2M application [31–34].

(iv) *Power control*: By carefully adjusting the transmission power of M2M devices, it is possible to reduce the energy required for data transmission. There are several techniques that can be implemented to control power and improve energy efficiency performance in M2M data transmission, such as power-aware routing, adaptive modulation and coding, and duty cycling [35].

(v) *Energy-efficient protocols*: There are numerous communication protocols that have been designed specifically to improve the EE of data transmission in a green M2M network. However, each of these protocols has its own unique set of advantages and disadvantages, and the most suitable protocol can be chosen based on the specific requirements of the M2M application. Details of the transmission protocols and technologies are discussed in the following sections.

Table 1. Data compression techniques.

Technique	Description	Advantages	Disadvantages
Huffman coding	Lossless data compression algorithm that encodes data using a variable-length prefix code based on character frequencies.	○ Simple to implement. ○ An adaptive algorithm ○ Good compression ratios. ○ Lossless compression.	○ Not suitable for highly correlated data. ○ Not suitable for streaming data. ○ Requires additional space to store the prefix code. ○ Slow (not suitable for real-time applications).
Lempel-Ziv-Welch (LZW) algorithm	Encodes data by identifying and replacing repeated patterns with references.	○ High compression ratio. ○ Suitable for both lossless and lossy compression.	○ Limited to text and other non-random data. ○ High computational power for some implementations. ○ Not suitable for streaming data.
Run-length encoding (RLE)	A technique that reduces data size by replacing repeated characters with a single character and a count of their occurrences.	○ Efficient for repetitive data. ○ Low computational complexity. ○ Low memory requirements. ○ Suitable for both lossless and lossy compression.	○ Not efficient for non-repetitive data. ○ Limited in compression ratio
Delta encoding	Encodes data by representing the difference between successive values rather than the values themselves.	○ High compression ratio for time series data and numerical data. ○ Low computational complexity. ○ Suitable for both lossless and lossy compression.	○ May not retain all original information. ○ May not be suitable for sensitive data.
Predictive coding	A technique that predicts values and encodes the difference between the prediction and actual value.	○ High compression ratio for time series and other correlated data. ○ Low computational complexity. ○ Suitable for both lossless and lossy compression.	○ May not retain all original information. ○ May not be suitable for sensitive data.
Transform coding	Uses a mathematical transformation to convert the data into a different domain, where it can be more efficiently encoded.	○ High compression ratio for certain types of data (e.g., images, audio). ○ Can be used for feature extraction. ○ Suitable for both lossless and lossy compression.	○ May not be suitable for streaming data. ○ High computational complexity. ○ May not retain all original information.

4.2. Power-Aware Scheduling

Power-aware scheduling is an important aspect of energy-efficient data transmission in M2M communications. By carefully managing the energy consumption of M2M devices, it is possible to extend the longevity of battery life of these devices and improve their overall performance and reliability. There are several approaches to power-aware scheduling in M2M communications, which can be summarized into two points: (i) downsize the energy consumption of M2M devices while still satisfying the required performance objectives. These algorithms can consider various factors, such as the remaining battery life of the M2M device, the importance of the data being transmitted, and the energy efficiency of the transmission technology [36]; (ii) use power-saving modes in M2M devices to reduce energy consumption during periods of low activity. These modes can include sleep modes, in which the device shuts down non-essential components to save power, and idle modes, in which the device reduces its operating frequency to conserve energy.

4.3. Offloading Computation/Task Offloading

Offloading computation refers to the process of transferring computation-intensive tasks from M2M devices to external resources in order to reduce energy consumption. This can be achieved through the use of edge, fog, or cloud computing, which allows M2M devices to access the resources of a remote server or a nearby edge device to perform complex tasks. There are several benefits to offloading computation for energy-efficient data transmission in M2M communications. One significant advantage is that lessening the workload on the M2M device's processor can lower the device's energy consumption [37]. Another benefit is that offloading computation can allow M2M devices to perform tasks that they would not be capable of performing on their own, due to limited resources such as processing power or memory [38]. This can enable M2M devices to perform more complex tasks, such as data analysis and machine learning, which can improve the overall functionality of the M2M system. There are several ways in which offloading computation for energy-efficient data transmission in M2M communications can be classified.

One way is based on the location of the resources or computing used for offloading [39] (as shown in Figure 5):

(i) *Edge-based offloading*: In this type of offloading, computation-intensive tasks are transferred to a nearby edge device, such as a gateway or a fog node. This can be done over a local area network (LAN) or a wireless network.
(ii) *Fog-based offloading*: A decentralized computing paradigm that gathers computing and data storage closer to the devices and users that need them, enabling more efficient and effective use of resources.
(iii) *Cloud-based offloading*: In this type of offloading, computation-intensive tasks are transferred to a remote server or cloud computing infrastructure. This can be done over the internet or a wide area network (WAN).

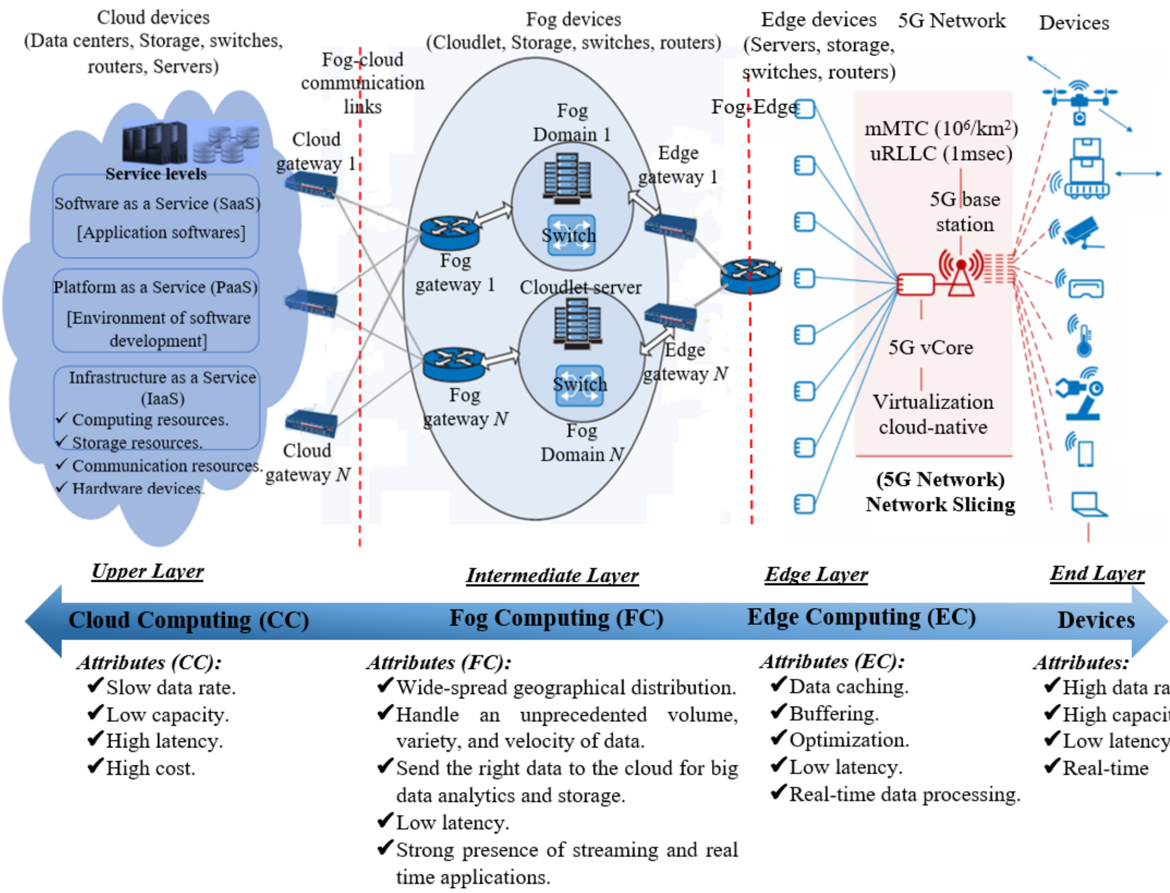

Figure 5. Architecture of computing layers.

Another way to classify offloading is based on the types of tasks that are offloaded [39]:

(i) *Data-intensive offloading*: In this type of offloading, tasks that involve large amounts of data, such as data analysis and machine learning, are transferred to external resources.
(ii) *Computation-intensive offloading*: In this type of offloading, tasks that require significant processing power, such as image processing and video encoding, are transferred to external resources.

4.4. Energy-Efficient Hardware

Energy-efficient hardware is important in M2M communication, where the IoT devices may require operating for long duration on a small battery or other limited power sources. Several hardware components are used to boost the energy efficiency of green M2M networks. Some of these components include:

(i) *Energy-efficient sensors (Green WSNs):* Some sensors including, temperature and humidity sensors, are known to be very power-hungry devices. Therefore, using energy-efficient sensors is the best way to reduce the power consumption in M2M systems. Details are given in Section 5.

(ii) *Energy-efficient radios (Green RFID):* Radio transceivers are a major source of power consumption in M2M devices. Thus, using an energy-efficient radio can improve the power consumption in M2M networks. Details are given in Section 5.

(iii) *Low-power microprocessors (Green MCUs and ICs):* By using a low-power microprocessor, the overall power expenditure of an M2M device can be considerably reduced. Details are presented in Section 6.

M2M technology primarily involves the use of sensors and RFID to collect data and transmit information over the network channel. These two components, RFID and sensor networking, are essential to the functioning of M2M systems. Accordingly, the following sections deal with discussing the role and importance of these two pillars in M2M technology.

5. Energy-Efficient and Eco-Sustainable Wireless Sensor Networks

Wireless sensors are small, inexpensive devices that run on batteries and are able to detect specific events or send regular updates about their surroundings. They are an important component of smart applications that utilize IoT technology. The deployment of a group of interconnected wireless sensors is referred to as a WSN. A typical WSN consists of multiple source nodes (wireless sensors) connected to a base station (sink node). In WSN topology, one of the sensor nodes acts as the network coordinator and assumes the role of the base station (BS) or head node (HN). The HN performs important network functions such as scheduling, resource allocation, interference management, and routing, and acts as a gateway to the larger network [40]. A summary of low-power wireless communication technologies for sensors can be found in [41]. In addition, Table 2 compares various wireless technologies using key parameters such as standard, energy consumption, frequency band, data rate, transmission range, and cost. Table 3 shows how well these technologies are suited for IoT applications.

Table 2. Summary comparison of the use of different wireless technologies for IoT applications.

Parameters	LoRa	Bluetooth	LR-WPAN	Mobile Communication	WiMAX	WiFi
Standard	LoRaWAN R1.0	IEEE 802.15.1	IEEE 802.15.4 (ZigBee)	2G-GSM, CDMA 3G-UMTS, CDMA2000 4G-LTE-A	IEEE 802.16	IEEE 802.11 a/c/b/d/g/n
Energy consumption	Very Low	Bluetooth: Medium; BLE: Very Low	Low	Medium	Medium	High
Frequency band	868/900 MHz	2.4 GHz	868/915 MHz, 2.4 GHz	865 MHz–2.6 GHz	2–66 GHz	5–60 GHz
Data rate	0.3–50 Kb/s	1–24 Mb/s	40–250 Kb/s	200 kb/s–1 Gb/s	1 Mb/s–1 Gb/s (Fixed) 50–100 Mb/s (mobile)	1 Mb/s–6.75 Gb/s
Transmission range	<30 Km	8–10 m	10–20 m	Entire cellular area	<50 Km	20–100 m
Cost	High	Low	Low	Medium	High	High

Table 3. The suitability of various wireless technologies for IoT applications [42,43].

Wireless Technology	Healthcare	Smart Cities	Smart Building	Automotive	Industry	Local Network (M2M)
Bluetooth (BLE)	very high	low	low	very low	very high	medium
LR-WPAN	medium	high	low	very low	low	high
LoRa	low	high	high	high	high	high
WiFi	low	high	medium	medium	low	high
WiMAX	low	very high	high	high	very high	high
Mobile communication	low	high	high	high	medium	very low

Wireless sensors are used to regularly and autonomously send data over a long period of time, especially in critical applications such as weather forecasting, traffic reporting, water quality monitoring, healthcare, and embedded systems. Wireless sensors are powered by batteries, but the cost of replacing or maintaining exhausted batteries can be prohibitive, especially in remote locations that have difficult terrain, making access to these sites challenging [44]. Due to geographical constraints, battery replacement may prove to be challenging in certain situations. Therefore, it is essential to develop energy-efficient solutions in order to extend battery life and reduce replacement costs for the sustainability of WSN. There have been numerous efforts to propose energy-efficient solutions for WSN. The major existing energy-saving mechanisms for green WSN are summarized in Figure 6. Below, a detailed discussion of the current energy-saving mechanisms will be presented with the goal of creating a more environmentally friendly WSN.

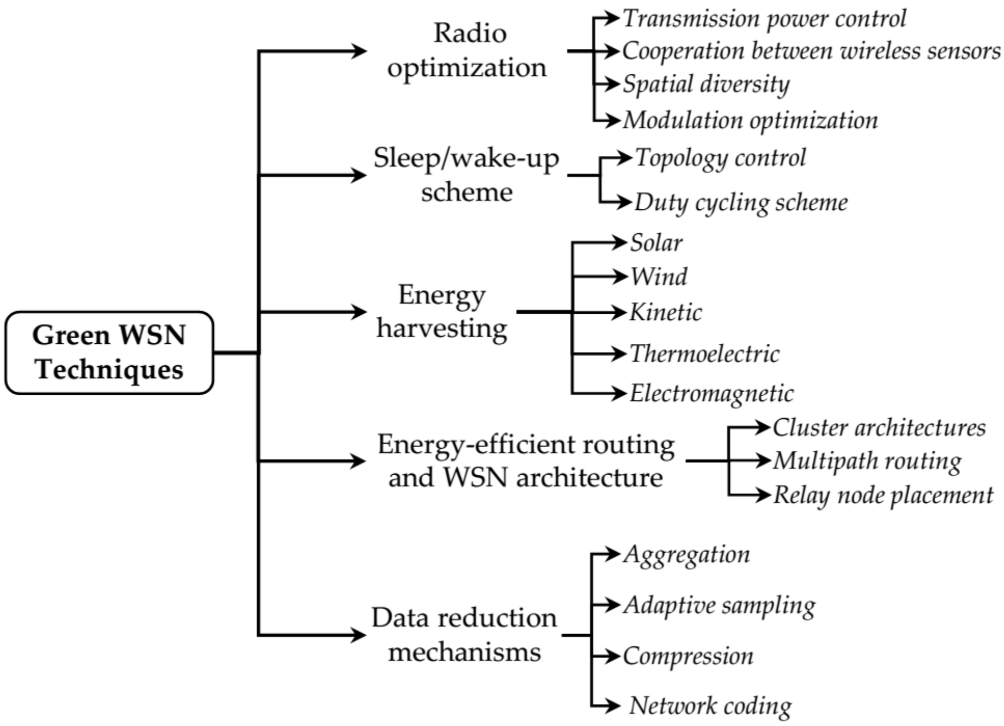

Figure 6. Classification of energy-efficient techniques for WSNs.

5.1. Radio Optimization Techniques

The radio unit is the main reason for the battery drain on sensor nodes. The energy consumption of the radio unit can be attributed to two factors: (i) power required for the circuit itself to function and (ii) power needed to transmit the signal. It is well-known that for shorter distances, the power required for the circuit itself to function is greater than the power needed to transmit the signal. However, for longer distances, the power required for the transmitted signal becomes the dominant factor in energy consumption. There have been several studies that have explored ways to improve energy efficiency by dynamically adjusting the transmission power level [45,46]. The authors in [47] proposed an energy-saving cooperative topology that allows nodes with higher remaining energy to increase their transmission power, which allows other nodes to decrease their transmission power. This can reduce interference and improve connectivity, but may also potentially increase the delay as more hops may be needed to forward a packet. Cooperative communications among neighboring sensor nodes can address the delay problem by creating a virtual multiple-antenna environment, providing spatial diversity and enabling retransmission of data. Cooperative communications among neighboring sensor nodes can improve the quality of the received signal by reducing the effects of multi-path fading and shadowing, extending the communication range among sensor nodes, and providing better energy savings and smaller end-to-end delays over certain transmission range distances. This has been reported in studies such as Cui et al. [48] and Jayaweera [49], who have compared the energy consumption of single input single output and virtual multiple-antenna (multiple input and multiple output) systems and found that the virtual multiple-antenna system offers better energy savings and smaller end-to-end delays under certain conditions. On the other hand, Cui et al. [50] have studied the relationship between energy consumption, transmission time, and bit error rate. The results showed that optimizing the transmission time can minimize the energy consumption needed to meet a given bit error rate and delay requirement. In addition, the authors in [51] conducted a comparison of the energy efficiency of three different modulation schemes to determine the optimal modulation scheme that achieves the lowest energy consumption at various distances between sensor nodes.

5.2. Sleep/Wake-Up Techniques

Turning off (entering sleep mode) unused wireless resources and devices has become a widely used method for reducing power consumption in the field of information and communications technology because it can save a significant amount of energy. To determine the system's average power consumption, we need to use Equation (1), which involves multiplying the sleep power by the percentage of time the system is in sleep mode, multiplying the active power by the percentage of time the system is active, and then adding the two products together before dividing the result by 100.

$$P_{avg} = \frac{(P_{sleep} \times \%time\ asleep) + (P_{active} \times \%time\ active)}{100} \tag{1}$$

The idea behind the proposed approach is to take advantage of the dense deployment of sensor nodes in a small coverage area, to make sensor nodes more energy efficient with extended battery life by turning sensor nodes on and off. When a system has a large sleep power compared to its active power, in this case, the system can be saving a large amount of energy. However, in some cases, the active power may be much larger than the sleep power, either because the power per event is high or because active power events occur frequently. However, in all cases, it is important to consider coverage in this approach, and ensure that it is still sufficient by the remaining active nodes. Misra et al. [52] proposed a solution that aims to minimize the energy consumption of the network while maintaining network coverage by activating only a subset of nodes with minimal overlap in their coverage areas. Karasabun et al. [53] modeled the issue of energy efficiency as a subset selection problem for collecting correlated data payload from active connected sensors. This approach takes advantage of spatial correlation to gather sensor information from non-active nodes through active nodes, making it a useful strategy.

Duty cycle-based protocols are generally considered to be very energy-efficient [54, 55]. The duty cycle approach, which switches a sensor node on and off depending on network activity, can be categorized into three types: (i) on-demand, (ii) asynchronous, and (iii) scheduled rendezvous. However, it is important to keep in mind that while a low-duty cycle can save a significant amount of energy, it may also result in lengthy communication delays. To minimize delays, protocol parameters can be adjusted before deployment for simplicity, although this approach may lead to reduced flexibility, or they can be dynamically altered to reflect current traffic conditions. Moreover, to optimize power consumption, the active period of nodes may depend on various factors such as traffic load, buffer overflows, delay requirements, or harvested energy, as discussed in [56].

5.3. Energy Harvesting, Batteries, and Wireless Charging Techniques

5.3.1. Energy Harvesting Sources

Advances in renewable energy technology can help to achieve the key features of wireless sensor energy sources, such as sustainability, reliability and reduction of greenhouse gas emissions [57]. In addition, the utilization of renewable energy technology holds great potential for enhancing the energy efficiency of wireless sensor networks situated in rural and remote regions where battery replacement may be problematic due to geographical barriers, such as challenging terrain that restricts access to these areas [58]. Solar cells are known for their high reliability and low maintenance requirements, and they can last for up to 20–30 years. Moreover, novel technologies have been introduced that enable sensors to collect energy from their environment, including wind and kinetic energy [59], and convert it into electrical energy that can be used directly or stored for later use. The characteristics and performance of renewable energy sources can vary significantly depending on the environment in which they are used. For example, outdoor renewable energy sources differ from those used indoors in industrial and commercial settings. A summary of indoor and outdoor energy sources and their properties is presented in Table 4. Nevertheless, it is essential to acknowledge that sensor nodes may exhibit an unequal distribution of remaining energy owing to variations in the amount of energy collected, and this must be taken into account when creating protocols [60].

Table 4. Summary of the indoor and outdoor energy harvesting sources and their characteristics.

Environment	Power Harvester			
	Solar Panel	*Wind Generator*	*Thermoelectric*	*Electromagnetic*
Power density of the indoor environment	100 μW/cm^2	35 μW/cm^2 @ wind speed < 1 m/s	100 μW/cm^2 @ 5 °C	4 μW/cm^3 @ human motion (Hz) 800 μW/cm^3 @ machine (kHz)
Power density of the outdoor environment	10 mW/cm^2	3.5 mW/cm^2 @ wind speed $\leq$ 8.4 m/s	3.5 mW/cm^2 @ 30 °C	

It is difficult to determine whether a specific IoT device would be a good candidate for energy harvesting without knowing more about its intended application and how it will operate in the system. However, there are certain categories of devices that are generally more or less suitable for energy harvesting, based on technical considerations, if not necessarily cost-effectiveness.

Overall, to efficiently manage the available power, renewable energy technology often relies on energy prediction schemes. However, to achieve high reliability, energy-saving mechanisms, in addition to renewable energy technology, may still be necessary. Sensors need to estimate the evolution of energy in order to adjust their behavior dynamically and survive until the next recharge cycle. As a result, they can optimize key parameters such as sampling rate, transmit power, and duty cycling to adapt their power consumption to the periodicity and magnitude of the harvestable energy source.

5.3.2. Battery Technologies for IoT/Sensor Devices

There are many different types of batteries that can be used in IoT devices, each with its own advantages and disadvantages. It is important to consider the specific requirements of the IoT device when selecting a battery, such as power consumption, size, and operating temperature. Other factors to consider include safety, cost, and the ability to replace or recharge the battery. Figure 7 summarizes some of the most common batteries used in IoT devices.

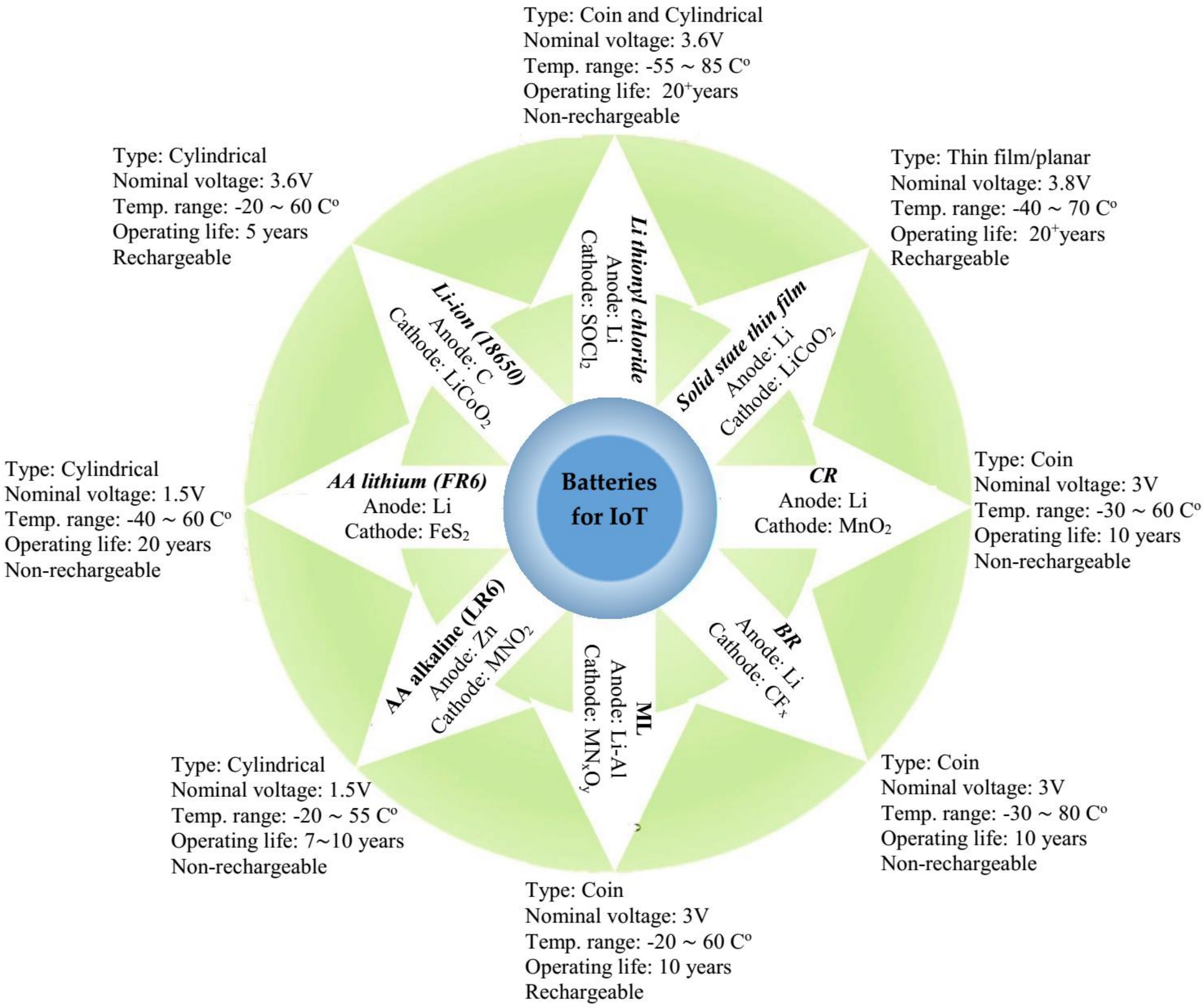

Figure 7. A selection of battery types commonly used in IoT/sensor devices.

The battery life cycle capacity can be calculated to determine if its total storage capacity over a specific number of charge/discharge cycles, at a specific depth of discharge (*DoD*), is sufficient for the task. The life cycle capacity is calculated as follows:

$$Life\ cycle\ capacity = Rated\ battery\ capacity \times Rated\ charge\_discharge\ cycle\ life \times DoD \quad (2)$$

Researchers are still working on developing protocols that take into account the deterioration of battery performance over time (such as leakage and storage loss), as this will impact the performance of the WSN.

5.3.3. Wireless Charging Techniques

Wireless power charging technology allows for more controlled recharging of network elements, resulting in increased sustainability and reliability in wireless sensor networks (WSNs). This concept has been implemented in various applications, including medical sensors, implantable devices, wireless sensor replenishment in concrete, and powering a ground sensor from an unmanned aerial vehicle. Energy transfer methods can be divided into two main categories: non-radiative coupling-based charging, such as magnetic inductive coupling, magnetic resonance coupling, and capacitive coupling; and radiative RF-based charging, which encompasses directive RF power beamforming and non-directive RF power transfer. Capacitive coupling is limited by the available area of the device, making it difficult to generate enough power density for charging, which poses a design challenge. Similarly, directive RF power beamforming requires knowledge of the energy receiver's exact location, which can be a limitation. Therefore, wireless charging is often achieved through alternative techniques such as magnetic inductive coupling, magnetic resonance coupling and non-directive RF radiation, which are less restrictive [61].

- The non-directive RF radiation technique uses electromagnetic radiation in the radio frequency range between 300 GHz and 3 kHz to transmit electric energy. This method is well suited for far-field communication; however, it has low efficiency in converting RF energy to DC energy when the harvested RF power is low. For further details on this technique and other RF power transfer methods, readers can refer to [62,63].
- Magnetic inductive coupling involves generating electrical energy between two coils that are tuned to resonate at the same frequency through magnetic coupling [64]. The magnetic field is used to transfer the required electric power. An illustration of the operating concept is depicted in Figure 8.

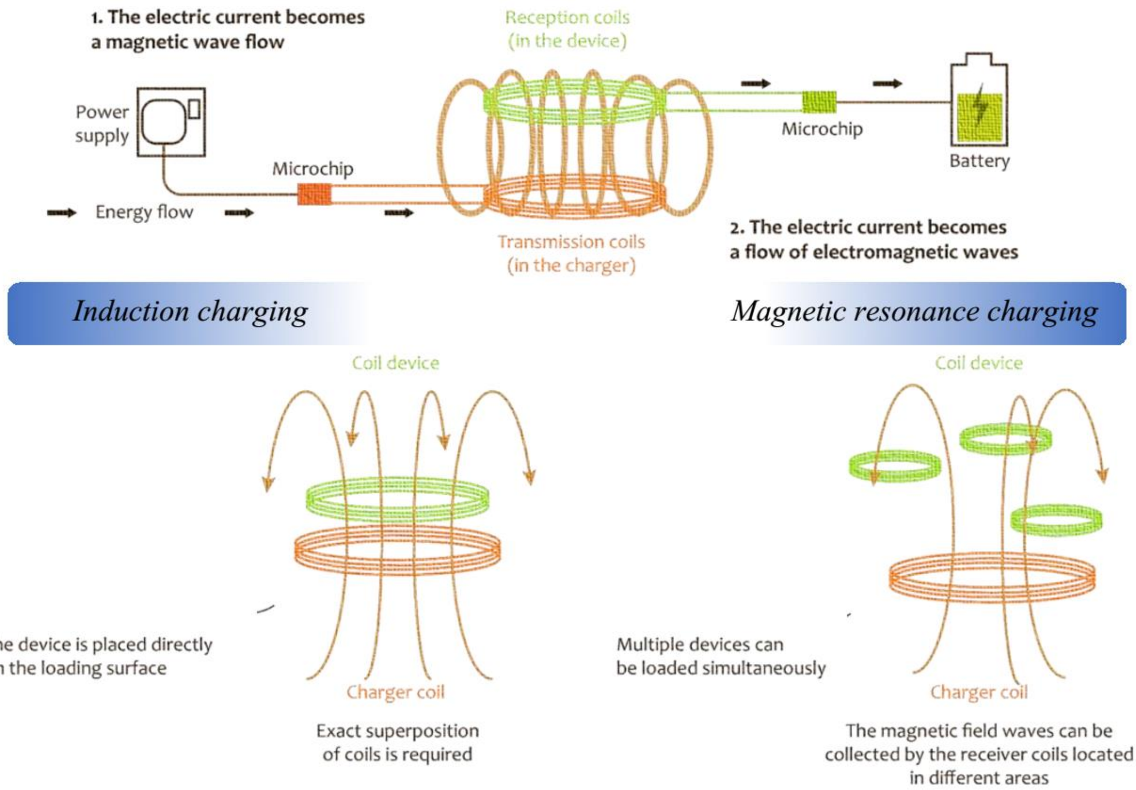

Figure 8. The operating concept of wireless charging by both magnetic inductive and magnetic resonance coupling.

- Magnetic resonance coupling involves the utilization of an evanescent field that generates and transmits electrical energy between two resonators [65]. To create this type of resonator, a capacitance is inserted between an induction coil. An illustration of the operating concept is depicted in Figure 8.

The inductive coupling and magnetic resonance coupling techniques both fall under the category of short-range communications, also known as near-field wireless communications (NFC). For more information on these, readers can refer to [66]. The high power conversion efficiency of near-field wireless transmission is well-known, and it is strongly influenced by the coupling coefficient and distance between the two coils/resonators. Nonetheless, the operational range (i.e., the distance between the transmitter and receiver) poses a significant challenge for near-field wireless transmission since the power diminishes rapidly as the distance between the devices increases [67]. Table 5 provides a summary of the advantages, disadvantages, and effective charging distance of three techniques: the non-directive RF radiation technique, magnetic inductive coupling, and magnetic resonance coupling. Based on information in existing reviews or research in the field [68,69], these factors were determined by the authors of this article.

Table 5. A summary of the advantages, disadvantages, and effective charging distance of the energy transfer techniques.

Technique	Advantages	Disadvantages	Charging Distance
Magnetic inductive coupling	○ Simple implementation. ○ Safe for humans.	○ Short charging distance. ○ Needs tight alignment between chargers and charging devices. ○ Heating effect.	Near-field.
Magnetic resonance coupling	○ Loose alignment. ○ Charging without the need for a direct line of sight. ○ Ability to charge multiple devices simultaneously with different power levels. ○ High charging efficiency.	○ Limited charging distance. ○ Complex implementation.	Near-field.
Non-directive RF radiation	○ Long-range charging, suited for far-field communication.	○ Requires a direct line of sight for charging. ○ Low charging efficiency. ○ Not safe when there is high exposure to RF density.	Far-field.

Several studies have examined the method of delivering energy wirelessly to sensor nodes that have been deployed in the field [70–72]. However, new challenges are introduced such as energy cooperation, as nodes can now share energy with their neighbors. In future wireless networks, nodes are expected to be able to both gather energy from their environment and transfer energy to other nodes, making the network self-sufficient [73]. Recent studies have shown that multi-hop energy transfer is possible [63], which presents new opportunities for designing wireless charging protocols, cooperative energy systems, and energy-efficient routing.

5.4. Energy-Efficient WSN Architecture and Routing Protocols

Cluster architecture is an effective method for increasing the energy efficiency of WSNs and ensuring scalability by maintaining a hierarchical structure. This approach involves grouping sensor nodes into clusters, with each cluster being led by a chosen node known as the cluster head. The cluster head is responsible for managing the activities of the members and communicating with other cluster heads or the base station [74,75]. This method of organization is illustrated in Figure 9.

Cluster architecture can improve energy saving in WSN in several ways:

- It decreases the communication distance within the cluster, which reduces the need for high transmission power.
- It reduces the number of transmissions by leveraging data fusion at the cluster head.
- It cuts down energy-consuming activities such as coordination and data aggregation by distributing them to the cluster head.
- It allows for some nodes to be powered off within the cluster, as the cluster head assumes forwarding responsibilities.
- It distributes energy consumption evenly among nodes by rotating the cluster head position.

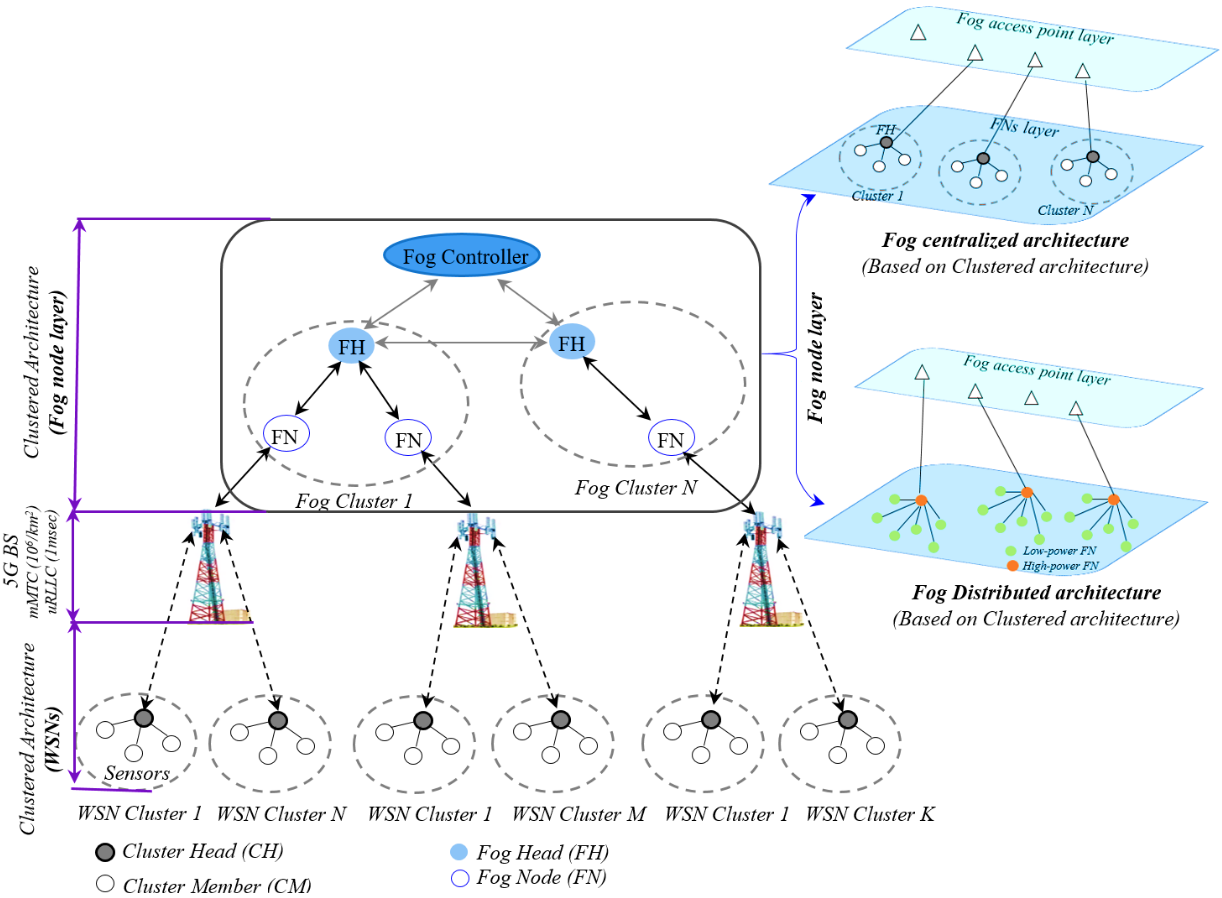

Figure 9. Cluster network architecture.

Unfortunately, uneven distribution of sensor nodes can result in depletion of energy in certain areas or create energy "holes". However, this can be mitigated by properly placing the nodes through optimal distribution or by adding a few relay nodes with increased capabilities. This improves energy balance among the nodes, avoids sensor hotspots, and ensures coverage and connectivity. Many studies have been conducted on finding the minimum number of relay nodes or placing them in the most efficient way to extend the network lifetime [76–78].

In general, single-path routing protocols are more straightforward compared to multipath routing protocols, However, they can quickly deplete the energy of nodes in the chosen path. Additionally, when a node runs out of power, a new route must be recalculated in single-path routing. On the other hand, multipath routing distributes energy among nodes by alternating forwarding nodes and also improves network reliability by providing alternative routes and allowing the network to recover quickly in case of failure. For more detailed information on multipath routing protocols for WSN, a comprehensive survey can be found in [79]. One energy-efficient multipath routing protocol for WSN is the energy-efficient multipath routing protocol (EEMRP), which is described in [80]. This protocol discovers multiple paths that do not share nodes by using a cost function based on the energy levels and hop distances of the nodes. and then, it allocates traffic to each of the selected paths. Additionally, the energy-efficient and collision aware (EECA) protocol, described in [81], puts forward two routes between a source and a sink that are not only node-disjoint but also free from collisions. Liu et al. [82] proposed two new energy-aware cost functions to enhance the energy balancing capability of the routing protocol by factoring in high energy consumption rates of nodes in hotspots: (i) The exponential and sine cost function based route (ESCFR) function, which amplifies small changes in remaining nodal energy into large changes in the cost function value. By giving preference to sensors with higher remaining energy during route selection, the ESCFR function promotes energy balance. (ii) The double cost function based route (DCFR) protocol factors in not only the remaining energy of nodes but also their energy consumption rate, which improve the energy-balancing performance of the routing protocol, even in networks with obstacles. Overall, the research results showed that multipath routing protocols were more energy-efficient than single-path routing protocols. Additionally, energy efficiency and the lifetime of the WSN can be further improved if the routing algorithms not only consider the shortest paths but also choose the next hop based on its remaining energy.

5.5. Aggregation and Reduction of the Data

Efficiently managing the amount of data transmitted to the sink nodes by reducing and aggregating it has been proposed as a method to enhance energy efficiency during the transmission process [44]. Data aggregation schemes [83] involve a node re-transmitting only the average or the minimum of the received data, which can reduce latency by decreasing traffic. An example of this would be, in a surveillance application, low-power acoustic detectors that can be utilized to detect intrusions, and when an event is detected, power-consuming cameras can be activated to obtain more detailed information [54]. Additionally, spatial correlation can be employed to decrease the sampling rate in areas where there is little variation in the sensed data. For recognizing human activities, Yan et al. [84] suggested that the data collection frequency should be adjusted to the user activity, as it is not necessary to sample at the same rate when the user is sitting or running. However, these techniques can also decrease the accuracy of the collected data, as the original data may not be recoverable by the sink, leading to a loss of information precision, depending on the aggregation function used [85]. Thus, it is not recommended to use these methods in applications requiring high accuracy. An alternative is adaptive sampling, which adjusts the sampling rate at each sensor while ensuring that application needs are met in terms of coverage or information precision.

On the other hand, network coding is used to decrease traffic in broadcast scenarios by sending a linear combination of multiple packets instead of a copy of each packet. Network coding makes use of the trade-off between computation and communication since communication is relatively slow and power-intensive compared to computation. Wang et al. [86] combined network coding with connected dominating sets to further reduce energy consumption in broadcast scenarios. AdapCode is a data dissemination protocol, where a node sends one message for every N messages received, thereby saving up to $(N-1)/N$ fraction of the bandwidth compared to naive flooding [87]. The receiver node can recover the original packets by using Gaussian elimination after successfully receiving N coded packets. In addition, AdapCode adapts the N value to the node density for improving reliability; as the density decreases, it becomes more difficult to recover enough packets to decode the data. To enhance the reliability further, it allows the nodes that received less than N packets to send a negative acknowledgement to retrieve missing data.

Ultimately, the choice of the most effective energy-efficient technique for green WSNs depends on several factors such as network topology, energy requirements, and application. It is crucial to assess the different techniques based on these factors and choose the most suitable one for the specific application. Nevertheless, Table 6 presents a summary of the energy-saving estimates of various green WSN techniques discussed in the literature.

Table 6. A summary of energy-saving estimates for different green WSNs techniques.

	Energy-Efficient Technique	Energy Savings	Advantages	Disadvantages
Radio Optimization Techniques	*Transmission power control*: Dynamic adjustment of transmission power to minimize energy consumption [46,88,89].	Up to 50% compared to a constant transmission power approach.	- Reducing energy consumption and prolonging network lifetime. - Improving network scalability and coverage - Improving network reliability by reducing interference and packet loss - Adapting to changes in network topology and environmental conditions	- Increasing complexity and overhead of network protocols. - Potentially increasing end-to-end latency and reducing throughput. - Depending on the specific algorithm used, it may require additional hardware or computational resources.
	Cooperation between wireless sensors: Collaborative data processing, routing, and sharing among neighboring sensors [89,90].	Up to 80% compared to independent sensor operation.	- Reducing redundancy and improving data accuracy. - Enhancing security and fault tolerance.	- Depending on the specific algorithm used, it may require additional hardware or computational resources. - Depending on the application, it may require additional communication overhead or latency.
	Spatial diversity: Involves using multiple antennas to transmit the same signal from different locations, which can reduce the transmission power required to achieve the same level of communication performance, leading to energy savings [91,92].	20–50%	- Increased energy efficiency and network lifetime. - Improved network coverage and reliability. - Reduced interference and signal fading.	- Requires additional hardware to implement. - Can increase network complexity. - May lead to higher deployment costs.
	Modulation optimization: Adjusts the modulation scheme based on the channel conditions and distance between nodes to reduce the energy consumption of transmissions while maintaining acceptable levels of communication performance [50,93].	Up to 60%	- Increased energy efficiency. - Improved data transmission rates.	- Complex algorithm design. - Requires sophisticated hardware. - Susceptible to interference.
Sleep/Wake-up Techniques	*Topology control:* Adjusting the transmission range; nodes can avoid unnecessary communication and reduce energy consumption [90,94,95].	15–60%	- Extends network lifetime. - Balances energy usage. - Reduces congestion.	- Increased complexity and overhead. - May impact network performance.
	Duty cycling: In which a sensor node is put into sleep mode for a certain period of time, known as the "duty cycle". During this sleep period, the node does not transmit or receive data, and its radio is turned off. When the sleep period ends, the node wakes up and resumes its normal operations [92,96,97].	30–50%	- Easy to implement. - Longer network lifetime.	- Reduced network throughput. - Increased latency. - Reduced network coverage.

Table 6. *Cont.*

	Energy-Efficient Technique	Energy Savings	Advantages	Disadvantages
Energy Harvesting Techniques [92,98,99].	Solar	70–90%	- Renewable source of energy. - Widely available. - Can be used in remote areas.	- Dependent on weather conditions (sunlight). - High initial cost of equipment.
	Wind	10–20%	- Renewable source of energy. - Can be used in remote areas.	- Dependent on wind speed. - High initial cost of equipment.
	Kinetic	20–40%	- Can be integrated with human activity. - Low initial cost of equipment.	- Limited availability of kinetic energy sources.
	Thermoelectric	5–10%	- Low-maintenance. - No moving parts.	- Low energy conversion efficiency. - Limited availability of heat sources.
	Electromagnetic	5–10%	- Can harvest energy from various sources. - Low-maintenance.	- Limited availability of electromagnetic energy sources.
Architecture and Routing Protocols [100–102].	Cluster architecture	20–40%	- Reduces energy consumption of nodes.	- Decrease network scalability.
	Multipath routing	20–30%	- Increases network lifetime and reliability.	- Requires extra resources and overhead.
	Relay node placement	30–50%	- Extends network coverage and reduces energy consumption.	- Increases network complexity and maintenance costs.
Data Reduction Techniques [92,103,104].	Aggregation	20–80%	- Reduces communication traffic and energy consumption.	- Increases data latency and processing overhead.
	Adaptive sampling	30–60%	- Reduces unnecessary data transmission and energy consumption.	- Requires extra resources and overhead.
	Compression	50–90%	- Reduces data size and energy consumption.	- Requires extra resources and processing overhead.
	Network coding	30–70%	- Increases data reliability and reduces energy consumption.	- Increase computational complexity.

6. Energy-Efficient Radio-Frequency Identification

An RFID setup includes unique identification tags (EPC), a reader, and middleware communication (Figure 10). RFID tags, which are made of a microchip and an antenna, are affixed to objects that need to be tracked. The RFID reader does not need to have a line of sight (LoS) to the tag, so the tag can be embedded within the object. The microchip on the RFID tag holds the electronic product code (EPC) and any other necessary information for tracking. These data can be tracked and read by RFID readers from any location. An RFID reader is a device, either stationary or portable, that is connected to a network and has an antenna. It transmits power, data, and commands to the RFID tags. The RFID reader serves as a gateway for objects tagged with RFID, allowing the data stored on the tags to be accessible to business systems. RFID systems have a limited transmission distance (a few meters) and operate on various frequencies, ranging from the low frequency band of 124–135 kHz to ultra-high frequencies of 860–960 MHz [105].

There are several different classifications of RFID tags, as given in Figure 11. However, we will focus in this study on the classifications in terms of energy.

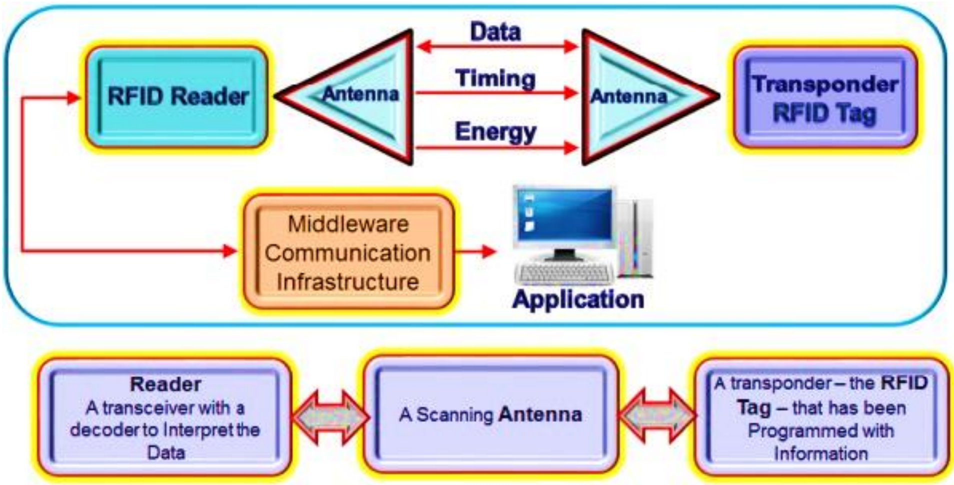

Figure 10. Operating principle of RFID system.

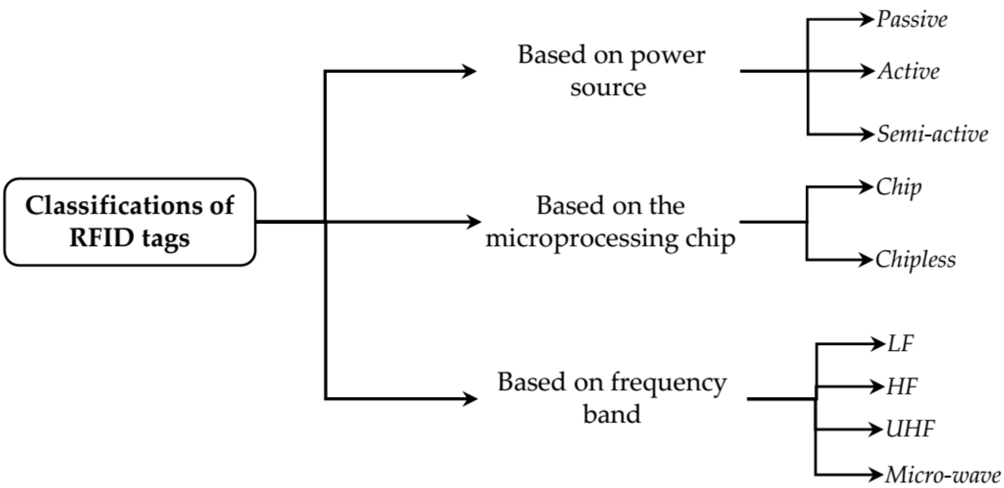

Figure 11. Classifications of RFID tags.

RFID tags can be separated based on their input power supply: Active RFID tags have an internal power source, typically a battery, and can transmit a signal over a long distance. Passive RFID tags do not have a power source and rely on energy from the RFID reader's signal to power the tag's microchip. These tags have a shorter transmission range. However, a semi-passive RFID tag has a power source but only uses it to power the microchip, not for transmitting a signal [106].

6.1. Passive RFID Systems

RFID passive systems use tags that are powered externally by electromagnetic energy from an RFID reader rather than having an internal power source. Passive RFID tags are commonly used in a wide range of applications such as inventory tracking, access control, timing events, smart labels, and supply chain management. They are also a cost-effective solution for many industries, as they have a lower cost per tag. Figure 12 illustrates the basic operation of a passive RFID system.

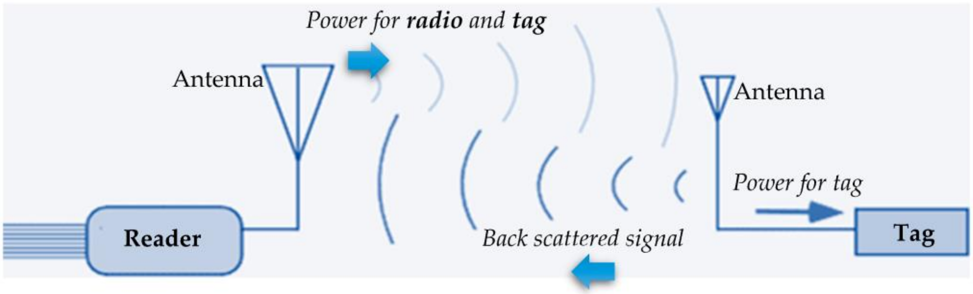

Figure 12. Passive RFID system.

As discussed in Section 5.3.3, there are three main techniques for transferring electromagnetic energy in RFID systems: the RF energy harvesting scheme, magnetic resonance coupling, and inductive coupling, which are presented in (Table 5). NFC is commonly used in passive RFID systems, and it can be either backscatter or inductive coupling. The RFID reader sends out a signal in the form of sinusoidal wave, which the tag antenna receives and converts into power using a rectifier circuit. The internal IC of the tag is powered by this energy, and it modulates the signal received and delivers it back to the reader. The tag solely modulates the signal that the reader sends it, not producing any signals of its own throughout this process. Detailed information on the backscattering fundamentals can be found in [107].

Passive RFID tags have low power consumption and are well-suited for wireless sensing applications. Notably, their operating range is limited, with the finest passive tags able to function at a distance of 7–15 m. This is mainly due to the weak electromagnetic induction-based communication principle. Additionally, path loss, which is a significant parameter in any wireless communication, also plays a pivotal role in limiting the operating range of RFID transmission in passive tags. Path loss is caused by a variety of factors such as refraction, free-space loss, diffraction, scattering, antenna height and location, reflection, weather conditions and surrounding environment. On the other hand, the inter-site distance between the transmitter and receiver and the height and position of antennas also play a vital role in path loss [108]. Therefore, selecting an appropriate path loss calculation model is crucial. In [109], the author extensively compared various channel path loss prediction models, for example, Hata, Friis, CCIR, etc., under different scenarios in various environments. However, such models are highly dependent on the system's operating frequency and application.

According to Ba et al. [110], RFID readers and WISP-Motes, passive RFID wake-up radios, are the main components of the network. The energy generated by the reader transmitter wakes up these passive RFID wake-up radios, allowing them to wake up the node. However, equipping all sensors with RFID readers is not practical due to their high power consumption, which limits their use to single-hop environments. Simulation results revealed that WISP-Motes can save a considerable amount of energy, but this comes at the cost of additional hardware and slower data transmission by increasing latency in data delivery. The advantages of this strategy have been illustrated by the authors in the context of a sparse delay-tolerant network with mobile elements that include RFID readers.

6.2. Active RFID Systems

Battery-powered RFID tags that continuously broadcast their own signal are used in an active RFID system. These tags, known as "beacons", are frequently used to precisely track the location of assets in real-time or in high-speed environments such as tolling. They are more expensive than passive tags but have a considerably larger scan range. Figure 13 summarizes the characteristics of the active RFID system.

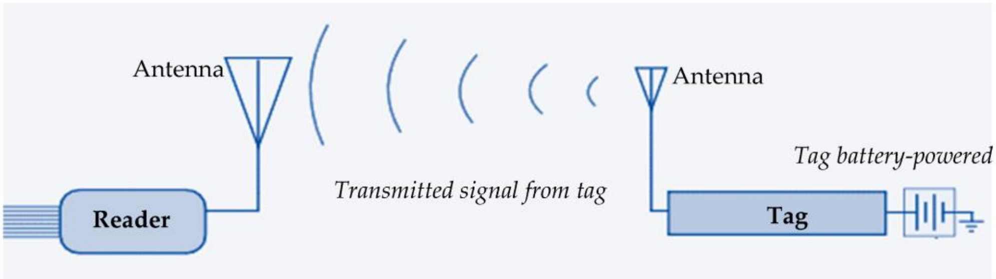

Figure 13. Active RFID system.

The energy storage system is the primary factor to take into account when considering an active RFID system. The two most common options are batteries and capacitors. Details are given in the subsequent paragraphs and summarized in Figure 14.

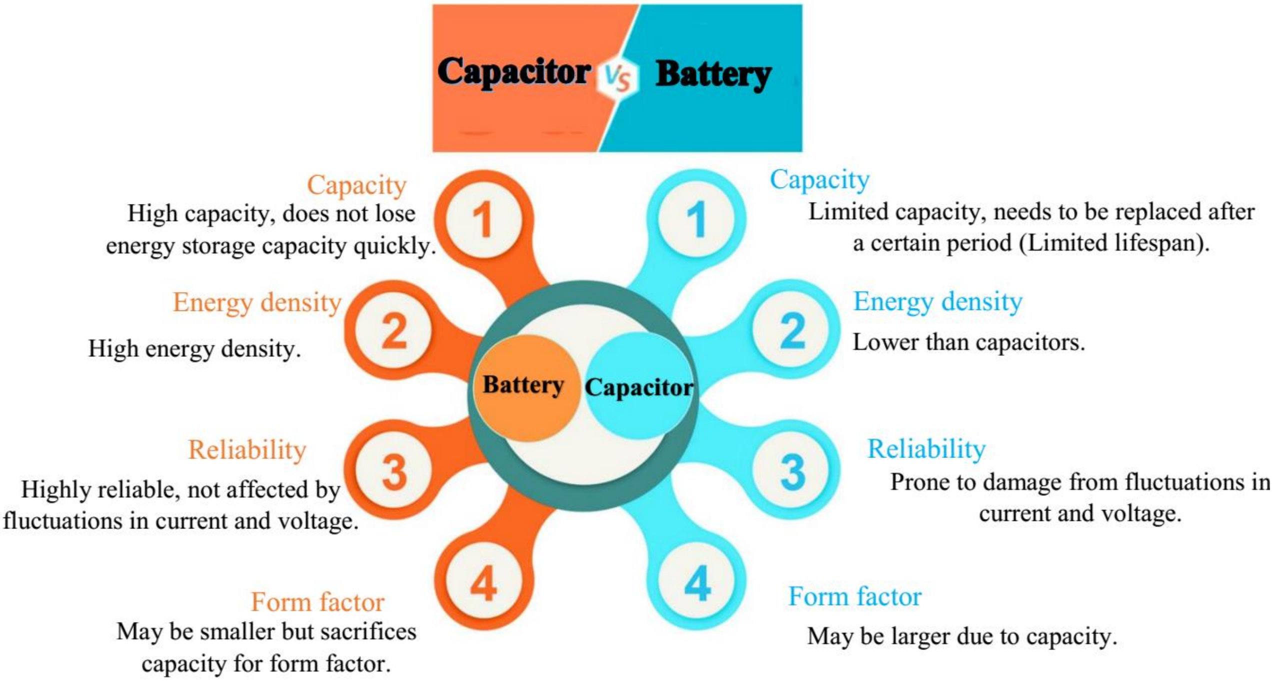

Figure 14. Comparison of energy storage options: batteries versus capacitors.

- ***Batteries:*** Batteries have been a popular power source for various devices since their invention and are still widely used today. However, they have a short lifespan and must be replaced after a certain period. Even rechargeable batteries lose their energy-retaining capabilities over time. Another important factor to consider when choosing a storage device is the form factor, which refers to the shape and size of the device. However, the relationship between form factor and capacity is often conflicting, as a larger capacity often means a larger device size [111]. As a result, batteries may not be the best option for RFID environments, where a small and flexible device is needed. Research has been conducted to find ways to develop compact energy storage devices that offer more flexibility while maintaining a high capacity. The emergence of thin film technology has made it possible for batteries to have the form factor needed for RFID applications [112]. This technology allows for the creation of electronic devices that are paper-thin and recognized as well-matched for thermo-electric micro-systems. Studies have shown that thin-film batteries are an ideal choice for applications where a thermal difference is present, such as the human body [113]. Overall, thin-film technology offers versatility and is a promising option for RFID tags.

- ***Capacitors:*** Capacitors are highly energy-efficient storage devices and do not diminish their capacity quickly, making them an ideal component for certain applications. However, the capacity of a capacitor is largely dependent on its size, and so capacitors often sacrifice form factors for a longer lifespan. Additionally, capacitors are unreliable to some extent because they are extremely susceptible to changes in current and voltage. However, recent advancements in capacitor storage technology have led to the development of ultra-capacitors and super-capacitors, which can store large amounts of energy and combine the reliability and performance of rechargeable batteries with the longevity of regular capacitors [114]. These ultra-capacitors are selected by designers because they have high energy densities that are many orders of magnitude higher than those of conventional capacitors. Some designs deploy a combination of storage devices, creating a hybrid system that combines the best features of different devices. These models have been investigated and tested using solar-powered wireless sensors with promising results [115]. The "Prometheus" model, for example, uses a dual-stage storage model in conjunction with a super-capacitor in the first stage and a lithium ion rechargeable battery in the second stage [116]. This system is regarded as a buffer for powering a Berkeley Telos mote extracted from a PV solar panel system, and experimental results have shown that it can run for up to 43 years at a 1% load and up to 1 year at a 100% load.

In summary, batteries are more suitable for long-term, steady power supply, while capacitors are better for high-power, short-term usage. The precise requirements of the RFID application will determine which option is best between the two.

On the other hand, references [6,10,117,118] focused on the transmission power issue. Reference [10] proposes the use of a sleep mode technique to downscale energy usage when the reader is not interrogating. Reference [6] proposes a protocol with the necessary algorithm in order to avoid overheating and save energy when the reader is not interrogating. A protocol and method are suggested in ref. [93,94] to prevent tag collisions during data transmission. While ref. [40,41] proposed dynamically adjusting the transmission power level in order to save energy, this method is less effective than using the sleep mode. Reducing the size of RFID tags should be taken into consideration to lessen the amount of non-degradable material required in their fabrication since environmental and energy concerns are the primary drivers behind green technologies such as printable, biodegradable and paper-based RFID tags [106].

7. Energy-Efficient Microcontroller Units and Integrated Circuits

A microcontroller unit (MCU) is an energy-efficient and cost-effective solution for embedded computing applications. It has programmable input/output peripherals, memory, and one or more processors, all integrated into a single circuit. This makes it ideal for use in IoT technology, particularly in devices powered by batteries or solar energy [119]. To improve energy efficiency, the data processing component should only be active for brief periods during which it reads, processes, and transmits information. The rest of the time, it remains inactive, a process known as duty cycling. The microcontroller unit normally waits for a sensor event or internal timer to wake it up, while it is in a deep sleep state for the majority of the time. Upon waking, the device restores power and clock functions, retrieves new data, processes it, and then returns to sleep after saving its state [108]. The power consumption pattern of a microcontroller commonly used in IoT applications is illustrated in Figure 15. Figure 16 provides an overview of key features for several MCUs frequently employed in ultra-low-power applications.

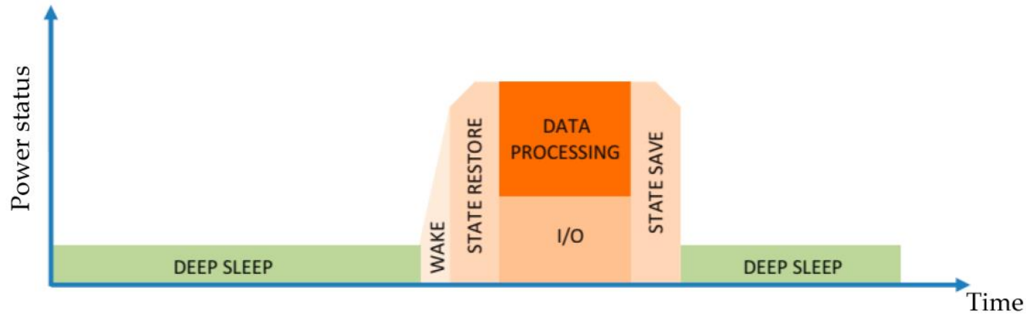

Figure 15. Demonstration of typical power consumption scenario of a microcontroller for generic IoT applications.

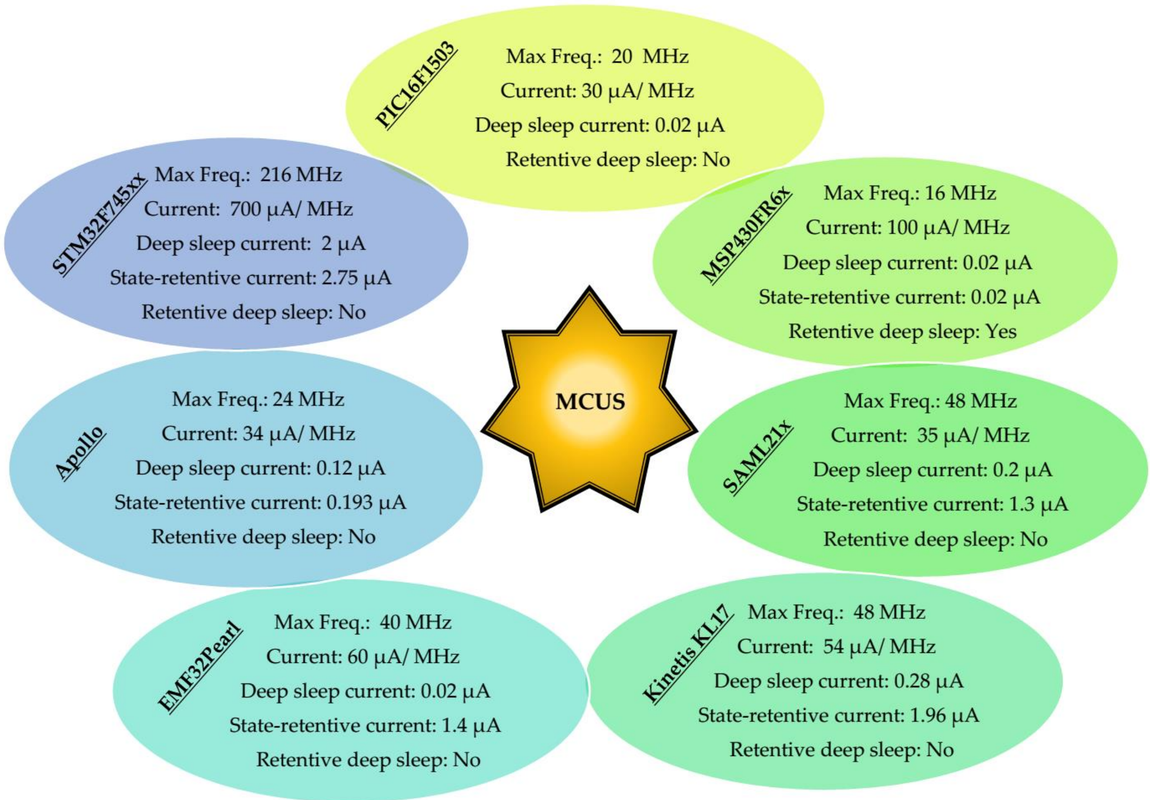

Figure 16. A summary of the key characteristics of MCUs commonly employed in ultra-low power applications.

However, many commercially available low-power microcontrollers are not able to cater to the performance needs of certain applications within the limitations of small coin batteries and energy-harvesting devices [120]. The latest CMOS ICs have the capability to significantly enhance energy efficiency by delivering the required functionality while maintaining a compact size and extremely low voltage. This can result in a remarkable reduction in overall system size and a lifespan increased by as much as ten times [121,122]. The strategy is to decrease the voltage supplied to the chips to a value just above the threshold voltage. Extensive research has been conducted on aggressive voltage scaling, including its limitations and drawbacks [123]. A major challenge with operating at low voltage levels is a decrease in performance, which can restrict the extent to which voltage scaling can be employed for a given processing need. Using application specific integrated circuits (ASICs) to implement hardwired functionality to get around the performance loss in ultra-low voltage devices is a popular way to solve this issue. With frequencies of tens to hundreds of KHz and power consumption ranging from a few to hundreds of microWatts, digital processing systems are capable of meeting the performance requirements of applications even at extremely low operating voltage by using specialized circuits. These specialized systems, which are developed as system-in-package (SiP) or system-on-chip (SoC) devices, combine analog signal processing, analog front end, digital signal processing, and power supply circuits (batteries, harvester, or both), resulting in highly compact designs [124]. The traditional fields of ultra-low power device applications, such as wearable or implanted sensors for health monitoring, have made extensive use of this dedicated ASIC approach [125–127]. While these devices greatly reduce power consumption, they lack flexibility because their functionality is limited to the specific service. Additionally, their performance cannot be adjusted, as they are created with a particular use case in mind. However, these restrictions can be lessened by introducing some runtime reconfigurability to the integrated circuits and by extending the working range through voltage and frequency scaling when the intended algorithms are more general and can be employed for numerous applications. There are numerous examples of this type of device, including vision sensors, where fundamental operations executed with specialized processors or dedicated accelerators can be shared among various applications [128,129]. However, it is crucial to note that sequential instruction execution and low operating frequencies may result in performance that is insufficient for the requirements of applications when operating at low voltage. The utilization of software parallelism is a key component to enhance the performance of ultra-low power processors while preserving a high level of flexibility. As it has been demonstrated that under some circumstances parallel processing at low voltage can be more energy-efficient than sequential computation at a higher voltage, using multicore platforms can benefit high application workloads [130]. High-end embedded applications, where multi-core architecture has become the standard, have made full use of this concept. Table 7 summarizes recent processors that are energy-efficient in terms of different features. Additionally, Figure 17 compares the power efficiency of multi-core processors vs. single-core processors at various operating points. Each operating point is dependent on the workload as well as the frequency and voltage required to achieve the performance shown. At low operating points (workload), single-core processors (blue line) are more power-efficient than multi-core processors (red line). This is because single-core processors can enter low-power states more easily than multi-core processors. When idle, single-core processors can enter sleep states, which significantly reduces power consumption, whereas multi-core processors often have to keep at least one core activity to manage system tasks [131]. However, as the operating point increases, multi-core processors become more power-efficient. This is because the clock frequency of single-core processors increases linearly with the operating point, while the power consumption increases quadratically. In contrast, the clock frequency of multi-core processors increases less steeply with the operating point, and power consumption increases at a slower rate [132]. In conclusion, the power efficiency of multi-core processors vs. single-core processors at various operating points is a complex topic that depends on several factors. At low operating points, single-core processors are more power-efficient, but as the operating point increases, multi-core processors become more power-efficient. The number of cores, cache size, workload, and power management techniques all play significant roles in the power efficiency of multi-core processors.

Table 7. Overview of recent processors that are both energy-efficient and ultra-low-power.

Feature \ Processor	MSP430	ReiSC	TMS320C64x	FRISBEE	ARM CortexM3	OpenRISC
Number of cores	1	1	1	1	64	4
Data format	16-bit	32-bit	32-bit VLIW	32-bit VLIW	32-bit	32-bit
Technology	CMOS	CMOS	CMOS	FD-SOI	CMOS	FD-SOI
VDD range (V)	0.4 (1.0)	(0.4–1.2)	0.6–1.0	0.4–1.3	0.65–1.15	0.32–1.2
Max freq. (MHz)	25	82.5	331	2600	80	825
Power dens. (μW/MHz)	7.7	10.2	409	62	317	20.7
Best Perf. (MOPS)	25	57.5	662	2600	1600	3300
Energy eff. (MOPS/ mW)	64.5	68.6	4.5	16	3.9	193

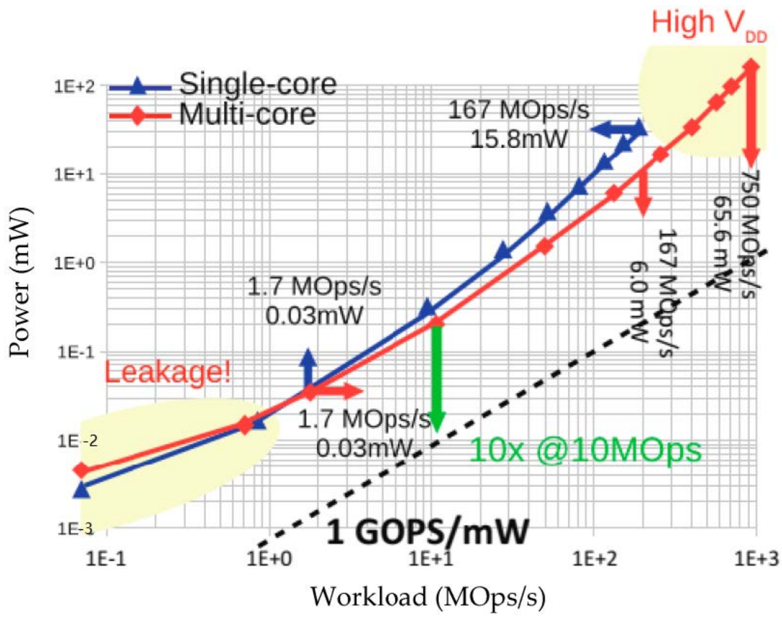

Figure 17. Comparison of the power efficiency of single-core vs. multi-core processors.

8. Potential Future Directions

We have identified several aspects for future research areas extracted from our study that are outlined in Figure 18. These research directions are further discussed and elaborated on in the following paragraphs.

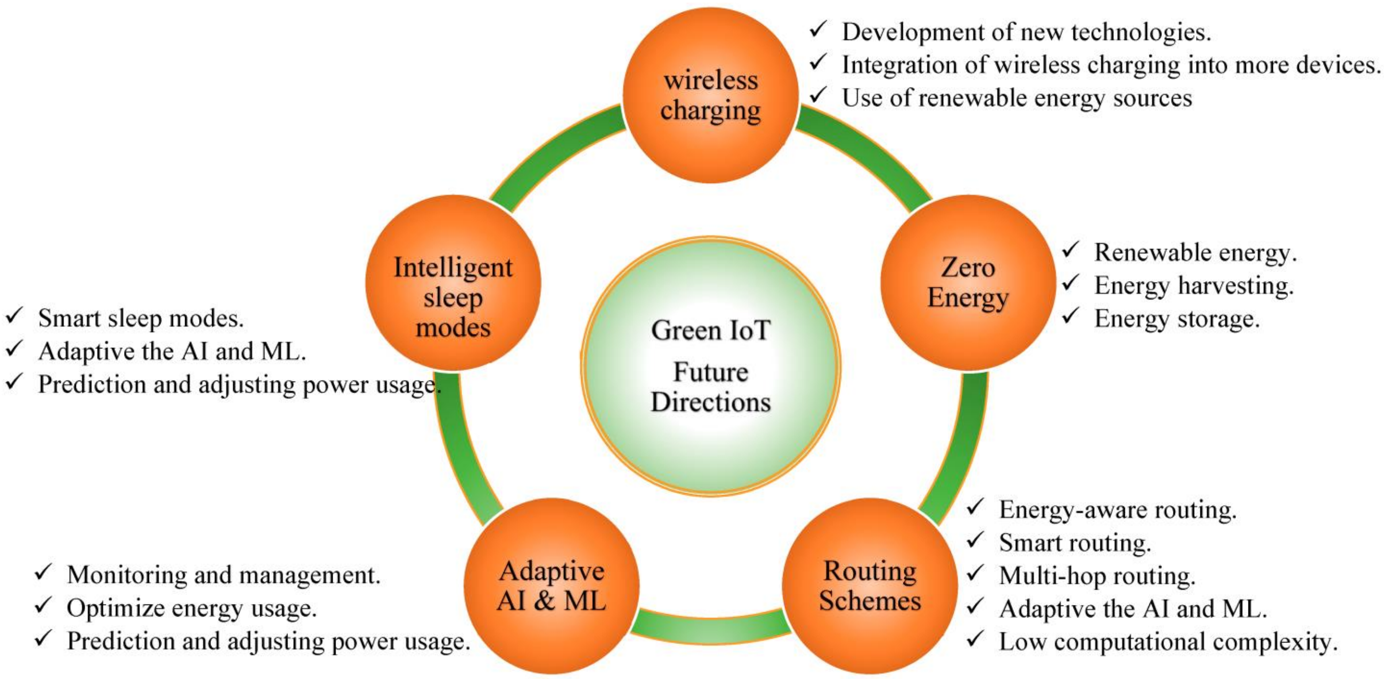

Figure 18. Potential future directions for green IoT.

(i) ***Zero energy***

Designing IoT devices to be powered by self-sustaining power sources such as solar, wind, or kinetic energy is an important area of research, as it enables the deployment of autonomous and sustainable IoT networks. The use of self-sustaining power sources can alleviate the challenge of battery replacement or recharging, which is a significant concern in IoT systems. One important consideration in designing IoT devices that can leverage self-sustaining power sources is the selection of appropriate energy-harvesting technologies. These technologies must be capable of harvesting energy from the surrounding environment and converting it into electrical energy that can be used to power the IoT device. Examples of such technologies include photovoltaic cells for solar energy harvesting, piezoelectric materials for kinetic energy harvesting, and small wind turbines for wind energy harvesting. In addition to energy harvesting technologies, the design of IoT devices that can leverage self-sustaining power sources must also take into account the power consumption of the device itself. IoT devices are typically designed to be energy-efficient to maximize battery life. However, when self-sustaining power sources are used, power consumption becomes less of a concern. As such, IoT devices designed for self-sustaining power sources may be designed to consume more power, enabling them to perform more computationally intensive tasks or transmit data more frequently. Another important consideration when designing IoT devices to be powered by self-sustaining power sources is the placement of the device in relation to the energy source. For example, solar-powered IoT devices must be placed in locations with sufficient exposure to sunlight to ensure adequate energy harvesting. Similarly, kinetic energy harvesting devices must be placed in locations where they can effectively capture kinetic energy.

On the other hand, exploring the implications of energy storage solutions, such as batteries or supercapacitors, to enable IoT devices to operate without a constant power source is an important area of research, as it can help to address the challenges of limited battery life and the need for constant charging or replacement. Batteries and supercapacitors are two types of energy storage solutions that can be used to power IoT devices. Batteries store energy chemically and are a common choice for many IoT devices due to their availability, low cost, and high energy density. Supercapacitors, on the other hand, store energy electrostatically and have a lower energy density than batteries but are capable of providing higher power densities and faster charge and discharge rates. One important consideration when exploring the use of energy storage solutions for IoT devices is the selection of an appropriate energy storage technology. The choice of energy storage technology will depend on factors such as the power requirements of the device, the expected operating conditions, and the desired lifetime of the device. For example, a device that requires high power output for short periods may be better suited to a supercapacitor, while a device that requires a more steady power supply may be better suited to a battery. Another important consideration when exploring the implications of energy storage solutions for IoT devices is the impact on device design. Energy storage solutions may require additional space and may add weight to the device, which can be a concern for devices that need to be small and lightweight. Additionally, the selection of an appropriate energy storage technology may impact the overall cost of the device, as well as the complexity of the device design. Despite these considerations, the use of energy storage solutions can provide numerous benefits for IoT devices. For example, the use of batteries or supercapacitors can enable IoT devices to operate without a constant power source, reducing the need for frequent charging or replacement. Additionally, energy storage solutions can improve the reliability and performance of IoT devices, providing a more stable power supply and improving overall device longevity.

(ii) ***Routing schemes***

The development of “smart” routing schemes that can dynamically adjust routes based on network conditions, traffic patterns, and energy availability is an important area of research for the future of IoT networks. Traditional routing schemes in IoT networks are typically static and do not adapt to changing network conditions or energy availability, which can lead to inefficient use of network resources and increased energy consumption. “Smart” routing schemes aim to address these challenges by utilizing real-time data and algorithms to dynamically adjust network routes based on network conditions, traffic patterns, and energy availability. These schemes can be implemented at various levels of the network, from the sensor nodes to the edge devices and gateways. At the sensor node level, “smart” routing schemes can be used to optimize the energy consumption of individual nodes by dynamically adjusting their transmission power and frequency based on the energy availability and network conditions. For example, nodes with low energy levels can reduce their transmission power and frequency to conserve energy, while nodes with high energy levels can increase their transmission power and frequency to improve network coverage. At the edge device and gateway level, "smart" routing schemes can be used to optimize the routing of data packets based on the network conditions and traffic patterns. For example, packets can be routed through nodes that have higher energy levels or better connectivity to reduce packet loss and improve network efficiency. One example of a "smart" routing scheme is the energy-aware routing protocol (EARP), which is designed for IoT networks with energy harvesting capabilities. EARP utilizes a decentralized approach to dynamically adjust network routes based on the energy availability and network conditions of individual nodes. The protocol uses a combination of metrics, including residual energy levels and link quality, to determine the optimal routing path for data packets. Another example of a "smart" routing scheme is the traffic-aware energy-efficient routing (TEER) protocol, which is designed for IoT networks with limited energy resources. TEER utilizes a centralized approach to dynamically adjust network routes based on traffic patterns and energy availability. The protocol uses a combination of metrics, including traffic density and residual energy levels, to determine the optimal routing path for data packets. Overall, the development of "smart" routing schemes that can dynamically adjust routes based on network conditions, traffic patterns, and energy availability is an important area of research for the future of IoT networks. These schemes can help to improve network efficiency, reduce energy consumption, and increase the longevity of IoT devices.

(iii) ***Adaptive AI and ML***

The development of AI-based energy management systems and machine learning algorithms for IoT devices is a rapidly evolving field that can significantly improve the energy efficiency and sustainability of IoT networks. These systems and algorithms can dynamically adjust and optimize power usage based on usage patterns, network conditions, and energy availability. AI-based energy management systems use machine learning algorithms to analyze data from IoT devices, such as usage patterns and energy consumption, to identify opportunities for energy optimization. These systems can also incorporate data from external sources, such as weather conditions or energy prices, to further optimize energy usage. The algorithms can learn from historical data and make predictions about future energy usage to adjust power usage in real-time. One application of AI-based energy management systems is in the optimization of energy usage in smart homes. These systems can analyze data from sensors, smart appliances, and energy storage systems to optimize energy usage in real-time. For example, these systems can adjust the temperature in a room based on occupancy patterns, weather conditions, and energy availability. They can also optimize the charging of energy storage systems to take advantage of lower energy prices or higher renewable energy availability. Another application of AI-based energy management systems is in the optimization of energy usage in smart cities. These systems can analyze data from sensors, traffic patterns, and energy consumption to optimize energy usage in real-time. For example, they can adjust the timing of traffic lights based on traffic patterns to reduce energy consumption and improve traffic flow. They can also optimize the use of energy storage systems to take advantage of renewable energy availability. Machine learning algorithms can also be used to optimize power usage in individual IoT devices. These algorithms can learn usage patterns and adjust power usage to minimize energy consumption while still meeting the device's operational requirements. For example, a machine learning algorithm can learn the usage patterns of a smart thermostat and adjust the temperature settings to minimize energy consumption while still maintaining comfort levels. In summary, the development of AI-based energy management systems and machine learning algorithms for IoT devices is an important area of research that can significantly improve the energy efficiency and sustainability of IoT networks. These systems and algorithms can dynamically adjust and optimize power usage based on usage patterns, network conditions, and energy availability, leading to reduced energy consumption, lower costs and increased longevity of IoT devices.

(iv) ***Intelligent sleep modes***

The development of intelligent sleep mode algorithms for IoT devices is an important area of research that can significantly improve the energy efficiency of these devices. Sleep mode is a power-saving state in which a device uses less power but remains operational. By developing intelligent sleep mode algorithms, IoT devices can dynamically adjust power usage based on usage patterns, network conditions, and energy available to achieve the optimal balance between power consumption and performance. Intelligent sleep mode algorithms use machine learning techniques to analyze data from the device and predict usage patterns. For example, the algorithm can learn when the device is typically used and when it is idle. Based on these data, the algorithm can adjust the device's power usage accordingly. If the device is likely to be idle for an extended period, the algorithm can switch the device to a deeper sleep mode to conserve more power. Another important aspect of intelligent sleep mode algorithms is their ability to adapt to changing network conditions. For example, if the device is experiencing poor network connectivity, the algorithm can reduce power consumption by reducing the frequency of network communications. Conversely, if the network conditions improve, the algorithm can increase the frequency of communications to improve performance. Energy availability is another important factor that intelligent sleep mode algorithms can take into account. For example, if the device is running low on battery power, the algorithm can adjust power usage to conserve energy. This might include reducing the brightness of the display or turning off non-essential features. Overall, the development of intelligent sleep mode algorithms is an important area of research that can significantly improve the energy efficiency of IoT devices. By dynamically adjusting power usage based on usage patterns, network conditions, and energy availability, these algorithms can help to achieve the optimal balance between power consumption and performance, leading to longer battery life and improved sustainability.

(v) ***Wireless charging***

The development of more efficient wireless charging technologies is an important area of research that can significantly improve the energy efficiency of charging electronic devices, leading to a reduction in environmental impact. Wireless charging is becoming increasingly popular, as it allows users to charge their devices without the need for cables or connectors. However, traditional wireless charging technologies have some limitations, including their energy efficiency. Research is ongoing to improve the efficiency of wireless charging, which can downscale the required energy to charge devices and decrease the environmental impact. One approach to improving the efficiency of wireless charging is to optimize the power transfer between the charger and the device being charged. This can be achieved through the use of advanced circuitry and control algorithms that monitor and adjust the power transfer to ensure that the charging process is as efficient as possible. Another approach to improving the efficiency of wireless charging is to increase the distance over which charging can occur. This can be achieved through the use of resonant wireless charging technologies that use magnetic resonance to transfer power over a greater distance. This technology can be used to charge multiple devices simultaneously, making it ideal for charging in public spaces such as airports and coffee shops. In addition to improving the efficiency of wireless charging, research is also ongoing to develop more sustainable wireless charging technologies. For example, some researchers are investigating the use of solar-powered wireless charging systems, which use photovoltaic cells to convert sunlight into electrical energy. These systems can be used to charge devices even in remote or off-grid locations, making them ideal for outdoor and wilderness environments.

9. Conclusions

Undoubtedly, the IoT will transform the whole ICT sector, alter the trajectory of technological development globally, and have a substantial effect on the economy in the years to come. This study provided a vision for eco-friendly and sustainable IoT and presents four (4) principles/frameworks to achieve that vision by tackle the energy efficiency issues related to hardware such as machine-to-machine communication, radio-frequency identification, microcontroller units, wireless sensor networks, integrated circuits, embedded systems, and processors. Finally, this study concludes with suggestions for potential future research directions to continue the pursuit of a vision for eco-friendly and sustainable IoT in the future.

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