Energy-Efficient IoT Communications for Environmental Monitoring: Perspectives and Challenges

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Abstract: Environmental monitoring is of great importance, and the Internet of Things (IoT) as a core supporting technology is also indispensable; among its key attributes, IoT communication energy consumption plays a critical role in ensuring stable system operation, while the capability of IoT to support both long-distance and short-distance monitoring is essential for achieving comprehensive and efficient environmental monitoring. Targeting the communication energy efficiency issues in the Internet of Things (IoT) for environmental monitoring, this paper systematically analyzes the energy consumption characteristics of short-range and long-range communication technologies, as well as their typical energy efficiency optimization mechanisms. It summarizes the strategies of different technologies for reducing wireless activation duration, transmission power, and data reporting frequency, and further discusses the limitations of existing research and future development directions. This paper can provide a reference for the design and deployment of high-energy-efficiency IoT systems for environmental monitoring.

1. Introduction

Environmental monitoring, as an important support for environmental safety and pollution control, has experienced significant development over the past 15 years. Internet of Things (IoT) technology has shown potential in the field of environmental monitoring, particularly in addressing the data latency issues of traditional monitoring systems while achieving significant results in reducing energy consumption and economic costs. IoT devices, through the deployment of numerous low-cost sensors, have made data capture easier and more economical. Combined with visualization capabilities, environmental data has become more intuitive and understandable [1-3]. The efficient data collection capabilities of IoT are particularly well-suited for environmental monitoring needs, enabling large-scale, high-density real-time monitoring [4].

Considering the energy constraints and maintenance cost pressures faced by IoT nodes in long-term deployment, energy efficiency has become a key bottleneck limiting system reliability and lifespan. Since IoT devices have limited energy storage, protecting them from security threats consumes additional energy, thereby depleting batteries and shortening network lifespan. Research on security solutions that strike a good balance between ensuring adequate security levels and reducing energy consumption remains scarce [5]. Therefore, developing efficient energy consumption data transmission schemes is crucial for enhancing IoT systems' capabilities in terms of throughput, energy efficiency, and self-management, which directly relates to extending the overall lifespan of IoT networks and the accuracy of environmental monitoring [6-8]. As shown in Fig.1, it represents a typical application scenario of the Internet of Things (IoT) for environmental monitoring, where multiple communication technologies cooperate to accomplish data collection and transmission.

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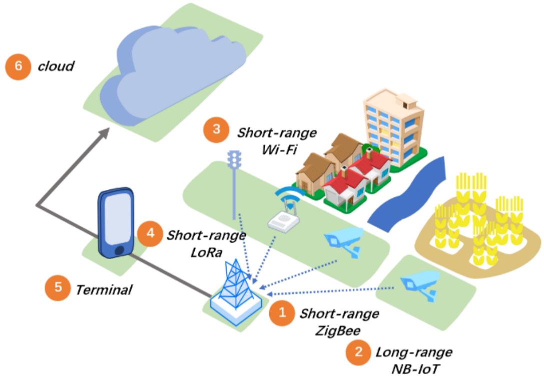

Fig. 1 Schematic Diagram of Iot Application for Environmental Monitoring Supported by Multiple Communication Modes

The main contributions of this article are summarized as follows: focusing on the communication energy efficiency of environmental monitoring IoT, it systematically analyzes the energy consumption sources of major communication technologies and their typical energy-saving methods. The rest of this paper is organized as follows. Section 2 presents the Background of the components of today's energy consumption and the various kinds of them. Section 3 presents the energy-efficient mechanisms of short-range communication. Section 4 presents the energy-efficient mechanisms of long-range communication. Section 5 presents the current limitations in IoT energy efficiency research and opportunities to the future. Section 6 presents the conclusion of the paper.

2. Background

2.1 The components of IoT energy consumption

The typical structure of IoT environmental monitoring nodes usually consists of four core components, as shown in Table 1:

Table 1: The components of the main structure of IoT nodes

Name	Function
Sensing layer	responsible for data collection, perceiving physical parameters in the environment through various sensors
Processing layer	perform local computation and analysis on the collected data
Communication layer	handle data transmission and interaction
Power Management	ensure the energy supply and optimized usage of the entire system

IoT accomplishes information interaction and data transmission between devices relying on wireless communication technologies.

The energy consumption of IoT nodes is mainly composed of the following core components:

Communication energy consumption is the primary component of IoT node energy consumption, typically accounting for 50-70% [9] of total energy consumption. Computational and sensing energy consumption includes MCU processing operations, sensor data collection, and signal conversion activities.

One of the main issues related to IoT is the need to develop an efficient energy-saving communication protocol. For energy-constrained nodes and edge nodes [10], minimizing energy consumption is a necessary condition for extending device service life and reducing operational costs.

2.2 Different kinds of communication technologies

The diversity of IoT environmental monitoring application scenarios determines the differences in communication technology requirements. Forest fire monitoring scenarios require coverage of vast forest areas, with communication distances reaching several kilometers or even tens of kilometers, and nodes are sparsely deployed with difficult maintenance. Therefore, the data rate requirements are relatively low, but the requirements for communication reliability and coverage are high [11]. River water quality monitoring scenarios typically deploy sensors linearly along river channels, requiring medium-distance communication capabilities [12-13]. These scenario differences directly lead to significant differences in communication overhead which indicates that there is no "one-size-fits-all" communication technology that can meet all scenario requirements.

Therefore, it is necessary to systematically compare the energy consumption performance of short-range communication technologies (such as ZigBee, BLE, Wi-Fi) with wide-area communication technologies (such as LoRa, NB-IoT, etc.). Understanding the classification of IoT applications and protocols using remote and short-range wireless technologies, which can perform wireless communication within different regional ranges [14], promotes the flexible deployment and expansion of IoT starting from the smallest area. Through comprehensive evaluation of different communication technologies in terms of energy consumption, coverage, rate, cost, etc., the optimal communication scheme can be selected for specific application scenarios, achieving a balance between system performance and energy efficiency. As shown in Fig. 2, different IoT communication technologies exhibit significant differences in terms of communication range and energy consumption characteristics.

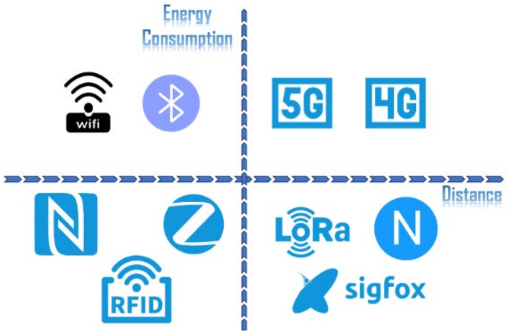

Fig. 2 Comparison of Range and Energy Consumption of Typical IoT Communication Technologies

Targeting the technologies above, this paper analyzes the mechanism of their energy efficiency optimization.

3. Energy Efficiency Optimization in Short-Range Communication

Short-range communication is mainly appropriate for aspects like local range, high-density nodes, and environmental monitoring tasks with frequent interactions, which is widely used in scenarios like the Wi-Fi-based environmental monitoring nodes that aim for more accurate data measurement [15], Greenhouse Agriculture Monitoring [16], and Building Energy Consumption Monitoring [17].As an important element of IoT, short-range communication shows its attacks in Low power consumption, cost effectiveness, facilitates rapid network establishment and is well-suited for high-density deployment [18]. This paper conducts a comparative analysis of the following mainstream short-range communication technologies for IoT applications: ZigBee, Wi-Fi, and Bluetooth.

3.1 Energy Efficiency Optimization in ZigBee

ZigBee stands as one of the most extensively adopted transceiver standards for wireless sensor networks [19]. For ZigBee networks, energy efficiency optimization primarily relies on three strategies: shortening the active time of wireless transceiver blocks, minimizing data transmission times, and prolonging the node sleep period, which contributes to a substantial reduction in node power consumption [20].

Onwunali et al. [21] analyzed the energy consumption model of ZigBee IEEE 802.15.4 nodes, divided the node states into four categories, namely transmit, receive, measure and sleep, and explicitly discussed the impact of duty cycle on total energy consumption and node lifetime. Based on the research conducted by Liu, Zhibin et al. [22], the energy consumption of ZigBee is mainly concentrated in the transmission phase of wireless transceivers, and its power consumption varies significantly with transmission distance, transmission frequency, and network stability. Experiments have demonstrated that the energy consumption of ZigBee is primarily determined by the activation duration of wireless modules and the number of retransmissions; thus, reducing the activation duration of transceivers and decreasing the number of retransmissions are the key directions for ZigBee energy-saving optimization.

3.2 Energy Efficiency Optimization for Bluetooth

Bluetooth is a wireless communication standard characterized by short-range transmission, low power consumption, and cost-effectiveness, which operates on radio frequency technology [23]. The energy consumption of BLE devices is mainly determined by broadcast events, connection events, and the active time of wireless transceivers; thus, energy efficiency optimization is generally carried out by reducing radio on-time, decreasing event trigger frequency, and improving low-power scheduling mechanisms [24-25].

Cortesi et al. [26] conducted a comparative study on the power consumption and latency of Bluetooth Mesh 5.0 and Wirepas Mesh on an experimental platform with 10 nodes. The experimental results showed that optimizing broadcast intervals, reducing event density, and decreasing idle listening time can significantly lower the average power consumption of BLE, which verifies that reducing the active duration of transceivers is the core direction for energy conservation. Tosi J, et al. [27] confirm that optimizing broadcast intervals, shortening idle listening time, and limiting network nodes (≤10) reduce BLE power consumption, which verifies that cutting unnecessary signal transmission frequency is the core energy-saving direction.

3.3 Energy Efficiency Optimization in Wi-Fi

Commercially referred to as Wi-Fi, IEEE 802.11 is a well-recognized standard for Wireless Local Area Networks (WLANs) [28]. The power consumption of Wi-Fi is mainly determined by continuous channel monitoring, high transmission power during data sending and receiving, and idle retention time required for maintaining connections. Therefore, energy efficiency optimization mainly focuses on reducing continuous monitoring time, adopting energy-saving modes to shorten wireless active duration, and utilizing low-power PHY/MAC features to cut down transmission costs [29].

Lim W S et al. [30] proposed a system called Power-Optimized Energy-efficient Mobility (POEM) and conducted extensive evaluations on an Android/Linux-based test platform. Experimental results show that POEM enables the Wi-Fi interface of mobile access points to enter sleep mode even during data transmission by leveraging the bandwidth asymmetry between Wi-Fi and WWAN interfaces and buffering packets received by the WWAN interface, which verifies that putting the Wi-Fi interface of mobile APs into sleep for a large proportion of time is an effective way to reduce Wi-Fi power consumption without significantly affecting system throughput or end-to-end latency. Zhang T et.al [31] introduced and evaluated a system-level power management approach for mobile handheld devices equipped with Wi-Fi (IEEE 802.11) interfaces. Experimental results show that this method can significantly extend the standby time of devices with Wi-Fi interfaces without modifying the Wi-Fi, upper-layer protocols and their implementations, verifying that system-level power management is an effective direction to reduce Wi-Fi power consumption for energy-constrained handheld devices.

4. Energy Efficiency Optimization in Long-Range Communication

In special scenarios which need large-scale, distributed environmental monitoring equipment, although short-range communication technologies have remarkable performance in energy efficiency, they have obvious limitations in terms of coverage range, network scale, and terrain adaptability. To achieve long-term cross-regional and cross-terrain monitoring, it is necessary to adopt wide-area communication technologies that feature strong coverage capability, long communication distance, and support for massive nodes. Currently, these technologies are mainly separated into three categories, as shown in Table 2:

Table 2: The Category of long-range communication

Name	Advantage	Sub-technology
Cellular IoT (CIoT)	low-cost, low-power, and scalable communication network [32]	NB-IoT, LTE-M,5G/6G
LPWAN	energy efficiency, high coverage, and cost efficiency [33]	LoRa, Sigfox
NTN	Energy efficiency, Data Analytics, Privacy and Security [34]	LEO, HAPS

4.1 Energy Efficiency Optimization for Cellular IoT

Cellular IoT (e.g., NB-IoT and 6G), as a technology oriented toward large-scale IoT connections within the cellular system, has its own energy consumption, which is affected by wireless transmission power, downlink monitoring cycles during connection establishment, and retransmission mechanisms. Therefore, its energy-saving optimization generally revolves around reducing connection establishment frequency, lowering transmission power, and decreasing data reporting frequency [35].

4.1.1 Energy Efficiency Optimization in 6G

6G, which serves as an efficient solution for overcoming security barriers in emerging application scenarios. Compared with previous wireless communication technologies, 6G has achieved remarkable improvements in energy consumption reduction and communication range extension [36-37].

Fowdur et al. [38] adopted machine learning-driven methods such as base station deployment optimization, adaptive operation mode switching, and intelligent beamforming to reduce the energy consumption of base stations and access networks, thereby improving the overall energy efficiency of 6G networks.

Hu, Ning, et al. [39] proposed an energy-efficient in-network computing paradigm for 6G that integrates network functions into general-purpose computing platforms to address the demand for energy-efficient computing in 6G networks.

4.1.2 Energy Efficiency Optimization for NB-IoT

Narrowband Internet of Things (NB-IoT) is a low-power wide-area network (LPWAN) technology based on a cellular network architecture. It is directly deployed on Global System for Mobile Communications (GSM), General Packet Radio Service (GPRS) or Long-Term Evolution (LTE) networks, and realizes low-cost, wide-coverage and low-power consumption connectivity for massive IoT terminals through narrowband radio frequency technology [40].

Nguyen et al. [41] designed an energy-efficient scheduling system by adopting an optimized Gated Recurrent Unit (GRU) model and the Narrowband Internet-of-Things (NB-IoT) protocol: the optimized GRU model generates tailored lighting dimming scenarios for each street based on environmental conditions and pedestrian traffic, and the NB-IoT protocol— a cellular-based technology that leverages existing LTE infrastructure—enables remote control of street light brightness.

4.2 Energy Efficiency Optimization for unlicensed LPWAN

Low-Power Wide-Area Network (LPWAN) technologies, represented by typical solutions such as LoRa and Sigfox, deliver ultra-low power consumption during long-distance communication by virtue of three core technical features: low-rate modulation, ultra-narrowband transmission, and extended data reporting cycles. Given that their energy consumption is predominantly governed by three key parameters—transmission duration, spreading factor, and reporting frequency—energy-saving optimization strategies for LPWANs typically revolve around four dimensions: rate adaptation, transmission power regulation, reduction of data reporting frequency, and data compression plus aggregation.

4.2.1 Energy Efficiency Optimization in LoRa

LoRa (Long Range) is a proprietary physical-layer communication technology for Low-Power Wide-Area Networks (LPWANs), which is based on spread spectrum modulation. By adopting Chirp Spread Spectrum (CSS) modulation, it enables long-distance data transmission of several kilometers without the need for relays, while featuring ultra-low power consumption to meet the requirements of low-rate and long-endurance communication for massive terminal devices in Internet of Things (IoT) scenarios [42].

Tu et al. [43] derived a closed framework for system-level energy efficiency modeling, analysis, and optimization in LoRa networks by leveraging stochastic geometry tools. This framework correlates the energy efficiency (EE) of LoRa with end device (ED) density and ED transmission power, revealing the variation trends of the EE curve with these two parameters and verifying the existence of an optimal transmission power that maximizes EE.

Lin z et al. [44] proposed a system EE analysis model that fully considers the impacts of multi-gateway, duty cycle, quasi-orthogonal spreading factor (SF), and capture effect; based on this model, the team studied the joint allocation optimization problem of channel (CH), spreading factor (SF) and transmission power (TP) to optimize system EE for uplink transmission, given the NP-hard complexity of this optimization problem.

4.2.2 Energy Efficiency Optimization in Sigfox

Sigfox adopts a connectionless broadcast mode with ultra-low power consumption and long transmission range, which performs optimally in IoT scenarios with small data transmission without retransmissions or acknowledgments [45].

Trendov S et al. [46] conducted a study on three LPWAN technologies (Sigfox, Narrowband Internet of Things (NB-IoT), and Long-Term Evolution for Machines (LTE-M)) using transceiver modules in a controlled environment as the experimental setup. This study establishes a multi-dimensional power consumption evaluation system for LPWAN technologies.

4.3 Energy Efficiency Optimization in NTN

As an important supplementary means for large-scale environmental monitoring in the future, Non-Terrestrial Networks (NTN)—including Low-Earth Orbit (LEO) satellites and High-Altitude Platform Stations (HAPS)—enable cross-regional monitoring via ultra-large coverage and space-air-ground integrated connectivity. However, the energy consumption of their terminal devices is significantly affected by three key factors: link loss over long-distance transmission, transmission power requirements, and access waiting cycles. Therefore, energy-saving optimization strategies mainly focus on four aspects: reducing link budget, designing lightweight access mechanisms, minimizing terminal transmission activities, and adopting reflection/relay communication technologies to cut down transmission power.

4.3.1 Energy Efficiency Optimization for LEO

LEO (Low Earth Orbit) satellites are artificial satellites operating in orbits 160–2000 kilometers above the Earth's surface, providing seamless large-scale coverage and high-quality signal access, while also facing technical challenges such as high mobility and limited payload budgets [47].

Xiao z et al. [48] proposed an energy-efficient resource allocation framework for AmBC-enabled NOMA IoV networks under imperfect Successive Interference Cancellation (SIC) decoding.

4.3.2 Energy Efficiency Optimization for HAPS

High-Altitude Platform Stations (HAPS) are aerial network nodes deployed in the stratosphere at an altitude of approximately 20 kilometers, which can serve as airborne communication base stations to provide communication services [49] .

Alqasir et al. [50] proposed an artificial neural network (ANN)-based method for energy-efficient (EE) operation of small base stations (SBSs) which demonstrates that the effectiveness of this method is close to that of the optimal scheme, the average mean squared error (MSE) of the proposed algorithm is only 1%, and it can achieve 10-step mobility prediction for UEs.

4.4 Energy Efficiency Optimization for Conclusion

This section compares the energy consumption characteristics and energy-saving strategies of three types of long-range communication technologies, namely Cellular IoT, LPWAN, and NTN. Although their energy consumption sources vary, energy conservation for all three technologies centers on three core approaches: reducing wireless active duration, lowering transmission power, and decreasing the frequency of data reporting. Cellular IoT is suitable for deep coverage scenarios, LPWAN is tailored for low-rate and long-distance monitoring applications, and NTN is applicable to remote and cross-regional scenarios. Their complementary nature lays a solid foundation for the subsequent construction of a multi-layer collaborative environmental monitoring network.

5. Limitzations

Based on the research represented in the first four chapters, we already know model of the consumption of IoT environmental monitoring, short-range and wide-area communication technologies, as well as their corresponding energy-saving mechanisms. However, research nowadays still has certain limitations, which restrict the energy efficiency performance of the system in practical deployment. Therefore, this chapter will summarize the limitations of current research and propose potential future research directions.

5.1 Current Limitations in IoT Energy Efficiency Research

5.1.1 Protocol-Level limitations

Existing IoT communication protocols are typically designed independently at the protocol layer, which leads to a lack of a collaborative optimization mechanism with the sensing, processing, and network layers. This makes it difficult for the system to achieve energy efficiency joint scheduling based on global states. Most energy-saving strategies rely on fixed parameter configurations (e.g., fixed duty cycles, fixed listening periods) and cannot dynamically adjust based on network load, environmental changes, or link quality, thus limiting the upper bound of energy efficiency optimization. Existing studies generally evaluate communication energy consumption under idealized or simplified channel conditions, without fully considering real-world factors such as interference, blockage, and dynamic terrain. This leads to discrepancies between theoretical results and energy consumption performance in practical deployments.

5.1.2 System-Level limitations

In high-density, heterogeneous environmental monitoring networks, multiple communication technologies (e.g., Wi-Fi, ZigBee, LoRa, NB-IoT) are commonly deployed in parallel. However, the lack of a unified cross-technology energy efficiency collaboration mechanism prevents the system from achieving overall optimization capabilities. Current energy efficiency optimization methods are mostly limited to a single-node or single-link perspective, lacking a global scheduling strategy for the entire network. As a result, they cannot dynamically coordinate resources and energy consumption based on network states. Although edge computing and in-network processing can reduce data volume, their integration with communication protocols and network scheduling layers remains insufficient, making it difficult to achieve energy efficiency balance between computing and communication.

5.1.3 Application-Level limitations

Environmental monitoring typically involves complex scenarios with multiple terrains, densities, and constraints. However, most existing studies validate their methods under idealized or single scenarios, resulting in insufficient applicability of these methods in real-world deployments. Most energy-saving algorithms do not fully consider practical application factors such as device lifecycle, maintenance costs, and long-term reliability, making energy-saving strategies unable to meet the monitoring requirements of long-term operation. Energy efficiency research and empirical data for extreme environments (e.g., remote mountains, oceans, deserts) are still lacking, leading to a significant gap between theoretical models and actual system performance.

5.2 Future Opportunities

5.2.1 AI-driven Energy Optimization

Artificial intelligence provides dynamic, adaptive decision-making capabilities for communication energy efficiency optimization, enabling automatic adjustment of transmission parameters based on link states, node loads, and environmental changes. Machine learning models can support multi-dimensional optimization such as power control, data sampling, and sleep scheduling, enabling the evolution of traditional fixed strategies toward intelligent scheduling. Typical directions include deep reinforcement learning (DRL)-based rate adaptation and machine learning (ML)-based sleep scheduling optimization.

5.2.2 Cross-layer Co-design

Cross-layer joint optimization can simultaneously consider the energy consumption contributions of sensing, processing, and communication, achieving overall rather than local energy efficiency improvements. By coordinating parameters such as sampling rates, data compression, and reporting periods, transmission loads can be effectively reduced, and end-to-end energy consumption can be lowered. Compared with traditional layered independent optimization methods, cross-layer design is more suitable for the multi-constraint, multi-objective comprehensive energy efficiency requirements in large-scale environmental monitoring.

5.2.3 Hybrid Multi-technology Networks

Future environmental monitoring systems will rely on the collaborative operation of multiple communication technologies (e.g., ZigBee, BLE, Wi-Fi, LoRa, NB-IoT, and NTN) to cover different distance and energy efficiency requirements. Through mechanisms such as cross-technology link selection, interface switching, and multi-hop collaboration, the overall network energy efficiency and reliability can be significantly improved. A layered fusion architecture allows terminals to select the most energy-efficient communication method in different scenarios, enabling flexible energy management.

Current IoT energy efficiency research still has shortcomings in terms of protocol adaptability, system synergy, and practical deployment validation. Future opportunities focus on: AI-driven intelligent energy saving, cross-layer collaboration, multi-communication technology integration, energy harvesting, and edge intelligence. These directions will promote more efficient and sustainable large-scale environmental monitoring systems.

6. Conclusion

This review systematically analyzes the energy consumption composition in IoT environmental monitoring and the energy efficiency characteristics of major communication technologies. It primarily compares the energy-saving mechanisms and applicable scenarios of various technologies, including short-range communication, LPWAN, cellular IoT, and NTN. Although these technologies differ significantly in link structure and protocol design, their energy-saving strategies all follow the common principles of reducing wireless activation duration, lowering transmission power, and decreasing reporting frequency. This review identifies limitations in areas such as communication protocols, system synergy, and practical deployment, and proposes future research directions including AI-driven approaches, adaptive cross-layer design, multi-technology integration, and energy harvesting. With the development of 6G, NTN, and edge intelligence, IoT systems for environmental monitoring are expected to achieve collaborative optimization with broader coverage, longer lifespans, and higher energy efficiency.

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