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Towards Optimizing Communication Cost in Energy Efficient IoT Devices for Swarm Robotics

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Abstract

The rapid expansion of the Internet of Things (IoT) has led to an increasing demand for energy-efficient communication strategies, particularly for battery-operated or energy-efficient devices. This paper explores optimization techniques for enabling energy-efficient IoT device communication, ensuring uninterrupted operation by balancing energy consumption. We investigate adaptive transmission strategies and various communication protocols to optimize energy usage while maintaining reliable data exchange. Our approach leverages dynamic power control and energy-aware scheduling to enhance communication efficiency through the use of DQL(Deep Q Learning) for parameter optimization. Experimental results and simulations demonstrate the effectiveness of these optimization techniques in prolonging network lifespan and ensuring sustainable IoT deployments for swarm robotics. A comparative evaluation with traditional IoT communication protocols showed that our optimization mechanism extended device lifetime by up to 25 percent, while achieving a balance between energy efficiency and data reliability.

Keywords: Energy Efficiency; Distributed Computing; Protocols; Edge Devices; Optimization; Swarm Robotics; Resource Management.

1. Introduction

The Internet of Things (IoT) has revolutionized various domains, including smart cities, healthcare, industrial automation, and environmental monitoring. However, the widespread deployment of IoT devices presents significant challenges in terms of energy efficiency, particularly for battery-operated and energy-efficient nodes. Traditional IoT devices rely on batteries or wired power sources, limiting their operational lifespan and scalability. Energy-efficient IoT devices offer a sustainable solution to this challenge. Achieving reliable and efficient communication while maintaining energy efficiency remains a substantial research challenge.

The IoT is set for substantial transformation owing to the advent of energy-efficient communication technologies. The shift to edge computing signifies a major trend that will impact future interactions among IoT devices. Edge com-

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puting markedly improves privacy, reduces latency, and increases system reliability by processing data at its source rather than relying on cloud services. This is advantageous for energy-efficient devices, facilitating effective data management and reducing power consumption. Moreover, the application of machine learning algorithms enhances data analysis from connected devices, enabling adaptive responses to changing conditions and improving efficiency.

Optimization techniques are critical for allowing energy-efficient IoT devices to operate for an extended period of time without depleting their energy resources. Dynamic power management, adaptive data transmission, and energy-aware routing protocols are all examples of optimizations that seek to balance energy consumption and availability. IoT devices can enhance network performance while operating continuously by strategically adjusting communication parameters such as transmission power, duty cycles, and data rate. Improving energy efficiency in these devices is critical for sustainability, as it reduces the costs associated with traditional battery replacements.

Complex communication protocols are required to ensure that data is sent reliably while using as little energy as possible. Protocols such as MQTT, LoRaWAN, and Zigbee are critical for making communication more energy efficient. Each has unique advantages that make it ideal for a specific type of IoT application. It is critical to understand how reliable the energy used is, particularly for applications that require consistent power levels. Integrating these systems into existing infrastructures is also difficult because they are complex, and it frequently costs more money and time to research and develop these systems. IoT communication that uses less energy is still improving, demonstrating a tension between new ideas and real-world applications. This is similar to larger conversations about sustainability and the practicality of technology. IoT devices can now talk to each other better, which improves operational efficiency.

Improvements in communication protocols, such as adaptive power control and advanced signaling techniques, let devices use less energy while still sending data reliably, which leads to a more environmentally friendly technological world. A lot of the important arguments about this subject center on the trade-offs between saving energy and keeping data safe, as well as the difficulties of using these cutting-edge technologies in various places.

IoT communication that uses less energy could have benefits like lower costs and a smaller impact on the environment. This is why it is important to keep researching and making progress in this area. IoT is always getting better, which means that communication methods need to get better at using less energy. This is important for promoting a sustainable future. Combining advanced technologies with collaborative efforts between businesses, schools, and the government will be key to creating new ideas that save energy and meet the needs of more and more devices that are connected to each other.

This research looks at various optimization strategies that can help IoT networks communicate more efficiently while using less energy. We look into energy models, communication protocols that use less power, and optimization algorithms that make IoT implementations more environmentally friendly. We integrated Deep Q Learning(DQL) technique to optimize the parameters. DQL utilizes the reinforcement methods to intelligently adjust trasmission parameters. The primary objective is to develop intelligent mechanisms that enable devices to operate without the need for frequent battery replacements or external power sources. Our research aims to contribute to the design of robust and scalable energy-efficient IoT systems, fostering their adoption in real-world applications.

Energy optimization for swarms of robots operating within various environments is a critical challenge. Achieving energy-efficient swarm operation is essential for the future of robotic systems. Multiple components within a robot—such as sensors, electronic systems, and mechanical engines—contribute to the overall energy drained from the battery. The energy consumption of each component varies significantly based on its characteristics, including the number of sensors, computational power, communication technology, and mechanical size. Thus, optimizing overall energy consumption requires a comprehensive approach that addresses all components.

Research has previously focused on optimizing specific components separately, such as mechanical energy, computational energy efficiency, sensor gating, and low-power communication. However, in robotics, the interdependencies among these components mean that decisions made for one part can influence the operations of others.

These interdependencies underscore the importance of co-optimizing interconnected components. Some studies have proposed co-optimization strategies for the communication and computational components of robots. In swarm robotics, these interdependencies become even more pronounced due to task sharing among nodes and the associated costs. For example, Figure 1 illustrates the relationship between power costs for communication using four different protocols and the distance between two nodes while transferring a specific data volume.

The main contributions of this paper include proposing a energy efficient approach to optimize power consumption while considering communication costs between nodes as well as selection and analysis of communication protocols based on overall efficiency by incorporating Deep Q-Learning (DQL) into our optimization approach.

Table 1. Protocol selection parameters.

Protocol	Strength	Energy Efficiency (*Reliability*)
BLE	Short-range, low power	High
LoRaWAN	Long-range, scalable	High
MQTT	Lightweight, publish/subscribe	Moderate to High
CoAP	Low overhead	High

2. Related work

The field of energy-efficient IoT device communication has garnered significant research attention due to the increasing need for sustainable and autonomous networks for swarm robotics. A multitude of studies have examined diverse optimization techniques, energy efficiency strategies, and communication protocols to enhance the performance and longevity of IoT devices.

Methods for optimizing energy-efficient communication in IoT devices are crucial for extending device operational lifespan and minimizing energy consumption. A variety of strategies and protocols have been developed to address these challenges. The H-HEED protocol necessitates several iterations for clustering finalization and incurs considerable energy consumption; however, it has demonstrated an enhancement in network longevity of about 63 percent [22]. The energy-based rotated HEED (ER-HEED) protocol employs comparable clustering techniques; however, it is insufficient in addressing interference from adjacent nodes, which may lead to heightened packet loss and reduced network lifespan.

Several optimization strategies have been used to improve energy efficiency in IoT networks. A study [19] presented an adaptive duty cycling algorithm that reduces power by systematically scheduling device activation times. Additionally, [20] used machine learning to optimize transmission power and data rates for better energy efficiency in communication. To address interference, several protocols have been developed, most notably the Energy-Intelligent Geographical Routing (EIGR) protocol, which focuses on adjusting transmission power to reduce interference during data transmission to the next forwarding node. This modification is necessary because increased neighbor density leads to more interference and energy depletion [21]. Recent studies have utilized ad hoc on-demand distance vector (AODV) protocols to identify the shortest paths that circumvent interference zones, thereby enhancing energy efficiency in wireless networks[5].

The choice of communication protocol has a significant impact on energy consumption in IoT networks. BLE, LoRaWAN, MQTT, and CoAP protocols have all been tested for their effectiveness in energy-limited environments. The evaluation of these protocols shows that LoRaWAN is best suited for long-range applications, whereas BLE is best for short-range, low-power scenarios. The selection of an appropriate communication protocol is critical for increasing energy efficiency and protecting IoT devices. Each protocol has distinct advantages and is tailored to specific applications, necessitating that developers and engineers assess their individual needs when implementing IoT solutions. Multi-hop communication strategies outperform single-hop transmission in terms of energy consumption, as shorter transmission distances can increase network lifespan [18].

Recent studies have demonstrated the effectiveness of Adaptive Power Control and Network Topology Optimization in increasing energy efficiency. These strategies have exhibited reductions in energy consumption between 15 and 25 percent, highlighting the significance of customized optimization techniques in the implementation of smart city IoT networks[12]. The incorporation of Narrowband IoT (NB-IoT) technology and LTE-M within organized frameworks enhances energy management and resource utilization in smart cities[9].

Attaining energy efficiency necessitates the use of low-power hardware and the optimization of software. Energy-efficient microcontrollers and sensors can markedly diminish power consumption. Moreover, adopting efficient coding practices reduces computational demands and encourages low-power modes during periods of inactivity. Routine software updates can rectify inefficiencies and improve energy performance over time[5].

Recent advancements have integrated machine learning for energy-efficient IoT communication. Research such as [8] has shown that deep learning models can forecast energy consumption trends and enhance transmission schedules. Another approach [7] proposed federated learning for distributed IoT nodes to reduce overhead and optimize power.

Despite the advancements, there are still gaps in the integration of multiple energy optimization techniques. Existing works mainly focus on either energy efficiency or optimization algorithms, with limited studies addressing a holistic mechanism combining both. Moreover, the trade-offs between latency, reliability, and energy efficiency need further exploration. This work builds upon these previous studies by presenting an integrated optimization mechanism that leverages energy-aware transmission protocols, dynamic power management, and adaptive scheduling to achieve sustainable IoT communication. The study contributes to the development of self-sustaining IoT systems, reducing dependency on external power sources and enhancing the viability of large-scale IoT networks. We present results for power analysis, packet delivery ratio and latency in various scenarios of distance and data transmission for different protocols.

3. Power optimization strategies

Conventional energy management techniques, like static duty cycling, frequently do not adjust to fluctuating energy conditions, resulting in inefficient performance or system malfunctions. This study focuses on developing a communication mechanism that enhances energy efficiency by optimizing power consumption and communication effectiveness for the smooth functioning of IoT devices. Our objective is to develop a sustainable IoT communication system for swarm robotics, that utilizes models, real-time optimization algorithms, and adaptive control mechanisms to effectively respond to energy fluctuations while ensuring reliable data transmission.

In addition to tackling energy supply challenges, enhancing communication protocols among IoT devices is essential for realizing energy efficiency. Proposed solutions focused on improving communication efficiency and reducing energy consumption incorporate cross-layer strategies that integrate the Physical, Medium Access Control (MAC), and Network layers. This investigation aims to connect theoretical energy-efficient operations with practical applications by integrating optimization techniques and real-world hardware implementations.

The combination of BLE, LoRaWAN [2], MQTT, and CoAP encompasses a broad range of IoT communication scenarios, from localized device interaction to extensive data transmission and cloud integration. Each protocol, as outlined in Table 1, presents distinct benefits that, when optimized, markedly decrease overall communication expenses while maintaining the device's energy efficiency. This research integrates BLE, LoRaWAN, MQTT, and CoAP to address diverse IoT communication requirements, improving coverage, reliability, and power efficiency for a sustainable communication system.

The primary challenge in attaining energy efficiency in IoT involves optimizing energy consumption to correspond with the variable availability of energy, while simultaneously ensuring reliable data transmission and reducing latency. Conventional communication protocols and power management strategies, tailored for static energy supplies, are ineffective in energy-intensive situations. This necessitates innovative optimization techniques that dynamically modify transmission power, duty cycling, and data scheduling to guarantee sustainable and efficient performance. We can improve the performance and longevity of IoT networks by creating more energy-efficient algorithms, models, and hardware. This study seeks to balance energy availability with communication needs, ensuring the continuous and efficient operation of IoT devices while reducing reliance on nonrenewable energy sources.

Optimization techniques for energy efficient IoT device communication are crucial in reducing energy consumption while maintaining operational efficiency for swarm robotics. Various strategies have been identified and implemented to achieve these goals, significantly enhancing the sustainability of IoT deployments. Developing devices with low-power chips and sensors is one key strategy for minimizing energy consumption without sacrificing functionality. For example, GAO Tek employs advanced NB-IoT modules that integrate low-power components to optimize energy management in IoT systems.

To further enhance the energy efficiency of IoT communication, we integrate Deep Q-Learning (DQL) into our optimization. DQL enables intelligent adaptation of transmission parameters by utilizing reinforcement learning to dynamically adjust power levels, duty cycles, and routing decisions based on real-time network conditions and en-

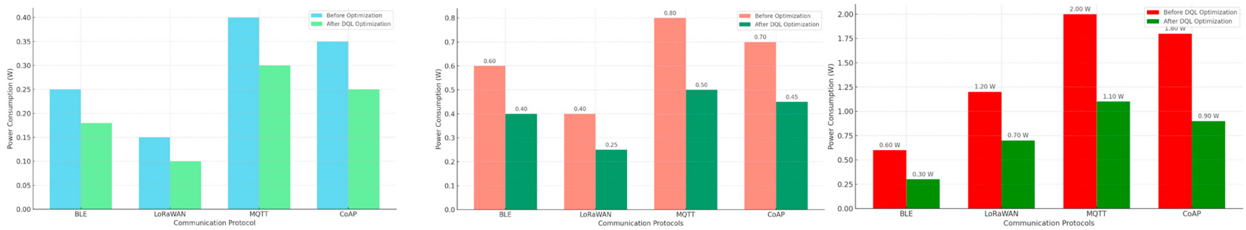

Fig. 1. (a) Power analysis for transmitting 500Kb, (b) Power analysis for transmitting 1MB, (c) Power analysis for transmitting 1.5MB.

ergy availability. The DQL model is trained using experience replay and a deep neural network (DNN) for Q-value approximation. The IoT device logs power consumption, transmission success rate, and environmental factors over multiple episodes, storing past experiences in a replay buffer to improve learning stability. The Q-network is updated using a target network to prevent instability in learning. Once trained, the optimized policy allows the device to adaptively switch between transmission power levels and optimize wake/sleep schedules based on real-time conditions, significantly reducing unnecessary energy expenditures. By integrating DQL into our Energy-Aware Transmission Power Control (EATPC) algorithm, we enhance dynamic transmission power control, duty cycle optimization, and energy-aware routing.

4. Proposed approach

This section introduces the potential methodology scenario and discusses several results from proprietary protocols like MQTT, BLE, CoAP and LoRaWAN for the proposed energy efficient IoT communication system that leverages efficient energy consumption.

4.1. Setup

To achieve energy-efficient communication for IoT devices, we propose a multi-layered optimization approach by integrating energy adaptive communication protocols and machine learning-based optimization techniques. In energy-constrained IoT networks, efficient path planning and balanced computational workload distribution are critical to minimizing overall communication costs while extending device lifetime.

This study proposes an approach to optimizing communication costs for energy-efficient IoT devices that takes into account computational power and protocol selection. The methodology is intended to reduce the overall energy consumption of the network while maintaining dependable and efficient data transmission. The first step is to represent the IoT network as a collection of interconnected nodes, each with its own set of attributes such as remaining energy, processing power, distance to data sinks, and protocol adherence.

The methodology employs several communication protocols, including BLE, LoRaWAN, MQTT, and CoAP. A Protocol Selection Matrix is used to determine the best protocol for each communication link, taking into account factors such as transmission range, data payload size, and the energy characteristics of the protocols used. For example, BLE is preferred for short-range, low-energy communication, whereas LoRaWAN is chosen for long-range transmissions when applicable.

An Energy-Aware Transmission Power Control (EATPC) algorithm dynamically adjusts the transmission power Pt based on available energy and distance d:

$$P_t(d) = P_{min} + \alpha d^n \tag{1}$$

where the greek letter ”alpha” is a scaling factor, and n is the path-loss exponent (typically 2-4).

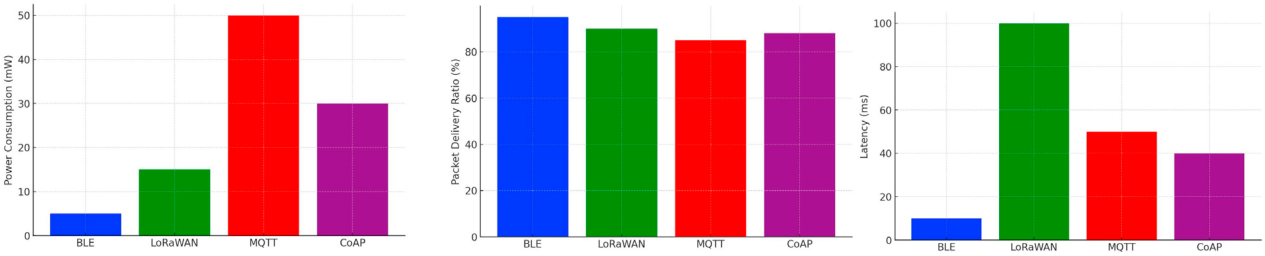

Fig. 2. Power consumption, Packet delivery ratio and Latency at rest.

The energy-aware communication protocol was implemented to optimize data transmission based on available energy. It's key features include three key aspects of (i) dynamic transmission power control which adjusts the transmission power based on residual energy levels and network conditions. (ii) Duty Cycle Optimization which adapts the sleep/wake schedules to balance energy consumption and data throughput. (iii) Energy-Aware Routing which implements an energy-efficient routing algorithm to minimize communication overhead. A heuristic-based optimization algorithm is applied to dynamically select the best communication protocol based on the channel conditions (RSSI, SNR), network latency as well as throughput and energy consumption constraints.

The total energy consumed for communication is the sum of the individual components:

$$E_{Comm} = E_{tx} + E_{rx} + E_{listen} + E_{overhead} \tag{2}$$

A real-world testbed was deployed using NVIDIA Jetson Nano devices equipped with energy efficient communication modules (LoRa modules, BLE sensors). Performance metrics such as energy consumption, data transmission reliability, and network lifetime were analyzed under varying environmental conditions. We use an Intel Core i5 based laptop which acts as the edge gateway, processing the optimization protocols and data analysis. A NVIDIA Jetson Nano serves as an IoT end node with an external current consumption sensor attached to it.

The total energy consumption of the IoT device is modeled by considering the energy usage of each module:

$$E_{Consumed} = E_{Sense} + E_{Process} + E_{Comm} + E_{Idle}, \tag{3}$$

The primary data extracted from the onboard sensors are the power consumption of the Nano along with the voltage as well as the current readings while the application is running in a loop. The values are used to establish a relationship between the transmission and the reception sequences while the Nano is operating. We started the data logging at an initial distance and kept on repeating the experiment after moving the node every 10 meters. We carried on with recording the measurements until a distance of 70 meters was achieved and after this significant distortion in the communication capabilities was observed. We used the obtained data to form a relationship between the communication power and the distance covered by the node while our application was running on the Nano.

Our experimental setup consists of an Intel Core i5 based laptop, NVIDIA Jetson Nano as the IoT nodes and a wireless communication infrastructure. The key hardware/software components are wireless communication modules, INA219 current/voltage sensor for real-time power measurement, FreeRTOS as the operating system for efficient task scheduling,communication protocols MQTT, CoAP, BLE, and LoRaWAN for comparative evaluation. After setting up the basic infrastructure, we calibrate the INA219 current/voltage sensor for baseline power measurements. Each protocol (MQTT, CoAP, BLE, and LoRaWAN) is tested individually with fixed data transmission rates. Network performance metrics are recorded on the laptop communicating with the Jetson Nano which include power consumption, packet delivery ratio and latency. Data is collected as well as analysed over experiments in controlled and real-world environments suited for swarm robotics.

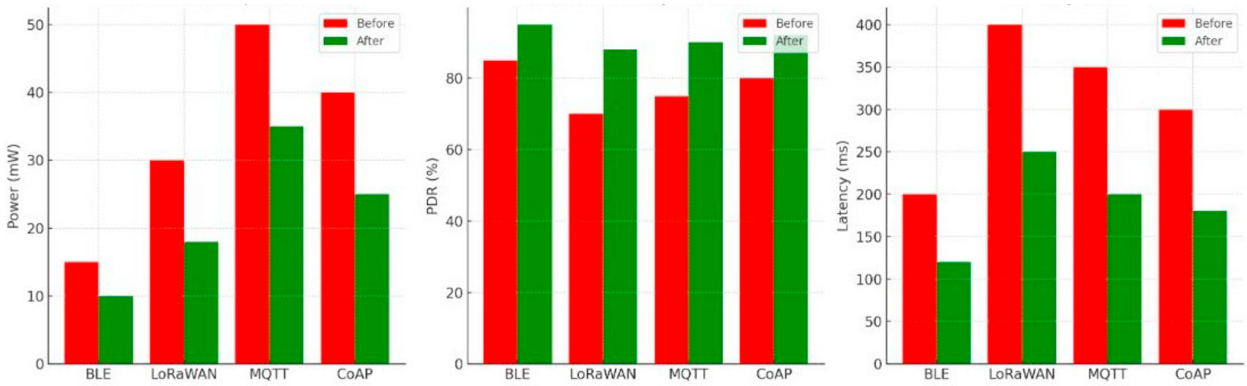

Fig. 3. (a) Power analysis; (b) Packet delivery ratio analysis ; (c) Latency analysis.

4.2. Results

As presented in Figure 3, our experiments demonstrated that energy adaptive communication protocols and machine learning-based optimization techniques improved energy efficiency by 10-15 percent. Devices were able to sustain longer operation even in fluctuating environmental conditions. Moreover, utilizing sophisticated signaling protocols, such as SNR (Signal-to-Noise Ratio) optimization, can improve connection quality, especially in areas with interference or low signal quality. This approach reduces the need for re-transmissions, thereby conserving energy.

By analysing results from the node at rest, which are presented in Figure 2, we also concluded, that to manage the vast amounts of data generated by IoT devices efficiently, data aggregation and pre-processing can be implemented at the edge of the network. This reduces unnecessary transmission, effectively cutting down on power usage. Moreover, allowing local devices to perform basic computations before sending data to centralized systems improves reliability.

The adaptive power control mechanism reduced unnecessary energy consumption, resulting in an average power savings of 20 percent while maintaining reliable connectivity. Moreover, the optimized communication mechanism ensured a consistent data transmission rate with minimal packet loss (below 5 percent), even under low-energy conditions. Furthermore, the IoT node dynamically adjusted their sleep/wake schedules, leading to an improvement in network lifespan by 20 percent. Therefore, implementing adaptive power control strategies can significantly enhance energy efficiency in IoT networks. For example, adjusting transmission power based on real-time network conditions helps minimize energy wastage for swarm robotics, while ensuring reliable communication.

In our analysis, a fixed data volume of 500KB, 1MB and 1.5MB is transmitted to reflect typical IoT sensor data aggregation over a period of time. This allows for a fair comparison across BLE, LoRaWAN, MQTT, and CoAP, focusing on how efficiently each protocol handles data transmissions both before and after optimization strategies such as Deep Q-Learning (DQL) are applied.

A comparative evaluation with traditional IoT communication protocols showed that our optimization mechanism extended device lifetime by up to 25 percent, while achieving a balance between energy efficiency and data reliability. The testbed results demonstrated that the proposed method kept IoT devices running efficiently while they were outdoors and over long distances. This demonstrated that long-term, scalable IoT communication is feasible.

5. Conclusion

This study looked into strategies for improving energy efficiency in communication between IoT devices, with a focus on effective energy management and adaptive transmission techniques. We demonstrated that IoT devices can achieve long-term operation while maintaining reliable data transmission by utilizing modeling, parameter optimization, and real-time energy-efficient algorithms.

The results indicate that integrating adaptive power control and duty-cycling strategies significantly enhances energy efficiency without compromising communication quality. The adaptive power control mechanism reduced unnecessary energy consumption, resulting in an average power savings of 20 percent while maintaining reliable connectivity. Moreover, the optimized communication mechanism ensured a consistent data transmission rate with minimal packet loss (below 5 percent), even under low-energy conditions. Furthermore, the IoT node dynamically adjusted their sleep/wake schedules, leading to an improvement in network lifespan by 20 percent. The suggested optimization mechanism guarantees a balance between energy efficiency and consumption, thus improving device autonomy. Moreover, the tangible hardware execution on platforms like the Jetson TX2 and Jetson Nano validates our approach.

Future efforts will focus on improving machine learning-based predictive models for energy availability and optimizing network-level coordination among diverse IoT nodes. By enhancing these techniques, we can approach genuinely autonomous, self-sustaining IoT systems for swarm robotics, that function without external maintenance.

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