Energy-Efficient Protocol Design for Wearable Healthcare IoT Devices

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Abstract: The increased need to maintain constant and real-time measurements of health has driven the use of Wearable Healthcare Internet of Things (WH-IoT) systems. Nevertheless, wearable devices have a significant drawback in the form of energy limitations, which limits their ability to operate sustainably especially in resource scarce conditions. In this paper, an energy-efficient communication protocol optimized to operate on WH-IoT and aimed at minimizing power consumption and ensuring data integrity, low latency and high reliability is presented. The suggested model combines adaptive sleep-wake scheduling, signal-aware duty cycling, and a lightweight MAC scheduling strategy, which are coordinated by a centralized gateway and cloud-based health analytics platform. The simulation findings reveal that the proposed protocol has better performance with respect to the current standards that use variation of power consumption like IEEE 802.15.4, B-MAC, and T-MAC in such important metrics like the average power consumption, packet delivery ratio (PDR), end-to-end delay, and network lifetime. A comparative analysis in details proves that the protocol is suitable to be used in the most important medical tools when the energy efficiency is crucial together with the real time responsiveness. The system is also scalable and robust thus a good option to implement in new smart healthcare ecosystems in the future.

1 INTRODUCTION

The integration of wearable computers and Internet of Things (IoT) has precipitated the development of Wearable Healthcare IoT (WH-IoT) systems that are transforming health monitoring and telemedicine with real-time physiological data gathering. These systems are much dependent on Body Area Networks (BANs) which are interconnections of physiological sensors printed on the body or implantation of body vital signs like heart rate, temperature, SpO 2, and ECG signals. As noted by Chen et al. (2011) [1], BANs form the basic role of empowering non-invasive, continuous health diagnostics using low-power wireless communication. Nevertheless, the design of these systems is very challenging due to the inherent resource limitations of these systems, e.g. limited battery life, processing power, and communication overhead.

As the demand of remote patient monitoring is becoming a reality, mobile health (m-Health) platforms are gaining popularity along with IoT technologies. These systems facilitate the smooth flow of health information to care providers, healthcare facilities, or cloud diagnostics or feedback systems. Almotiri et al. (2016) [2] highlight that the combination of m-Health and IoT allows delivering care that is independent of location and is particularly relevant to the management of chronic diseases and provided to the elderly. In a similar manner, Kaidi et al. (2024) [3] give an extensive overview of wireless healthcare monitoring systems and list the essential components of the system, including sensor nodes, gateway, middleware, and cloud services. Such systems however require very strict Quality of Service (QoS) guarantees such as low latency and high reliability and hence even more strain on energy consumption at sensor level.

Although wearable computing solutions continue to proliferate (Fortino et al., 2018) [4], current protocol designs are usually generic and not adaptive, and do not address the requirements of the biomedical data flows. Further, energy usage is turned out to be a significant bottleneck as it requires constant sensing, safe communication, and real-time analytics. Islam et al. (2015) [5] express the increasing complexity of the networks based on IoT health care, and mention the multi-layered challenges of communication, power management, and security.

The most important thing in healthcare applications is security and data integrity. Biomedical data is dynamic and sensitive, which requires a strong authentication and access control system. Ding et al. (2021) [6] suggest group authentication and key distribution strategies that are applicable in networks of Wireless Body Area Networks (WBANs) to guarantee a secure exchange of data. In line with this, Hameed et al. (2021) [7] carry out a systematic review of Internet of Medical Things (IoMT) privacy concerns, and emphasize the presence of machine learning solutions in intrusion detection and anomaly classification. These views confirm the dualism between energy efficiency and the security of the WH-IoT protocol design.

Therefore, there is a definite gap in research to create cross-layer energy-efficient protocols, lightweight and context-aware in specific to WH-IoT ecosystems. The gap that this paper seeks to fill is in the development of an adaptive protocol design that minimizes energy consumption and ensures data fidelity, low transmission delay, and privacy.

2 LITERATURE REVIEW

The introduction of Wireless Body Area Networks (WBANs) into the wearable healthcare has provided groundbreaking power in the continuous physiological monitoring, real-time diagnostics and proactive health management. A major limitation however is the energy efficiency of these networks especially systems that require high data fidelity, security as well as responsiveness. According to Latré et al. (2011) [8], mobility, proximity, and a heterogeneous communication environment limits the use of WBANs, requiring special protocol designs capable of supporting the needs of healthcare.

Much literature has been conducted to identify the use of Medium Access Control (MAC) protocols in controlling energy consumption within WBANs. Hayat et al. (2012) [9] note that the MAC design that is energy efficient can dramatically cut idle listens, overhearing and control overhead. Their categorization of MAC protocols as contention-based, TDMA-based and hybrid provides the basis of optimization strategies that are responsive to the dynamics of health data traffic. This is further extended by Javaid et al. (2013) [10] who give a detailed overview of MAC schemes in a healthcare setting. These involve sleep scheduling protocols, low-duty cycling protocols, and critical data prioritization protocols. But, as Marinkovic et al. (2009) [11] note, trade-offs between latency and energy conservation undermine many of these protocols. Their offered low-duty cycle MAC protocol showed better energy-saving benefits by adding wake-up radios, but scalability and adaptability are still an issue.

On a system scale, recent research adopted a cross-layer strategy in dealing with the energy issue in the Internet of Wearable Things (IoWT). Qaim et al. (2020) [12] give a systematic review of energy optimization approaches that cover data aggregation, event-based sensing, and load balancing. Their results bring to the fore the fact that MAC-level optimization is not complete and should be supplemented with smart sensing and dynamic routing. Gravina and Fortino (2020) [13] also support the role played by wearable body sensor networks in facilitating context-aware applications and promote dynamic protocol architectures that are able to react to environmental and physiological changes in real time.

As the complexity of data flows in WH-IoT becomes more complicated, the idea of smart e-health gateways has become essential. These gateways do not just facilitate aggregation of data but also they are also edge processors that minimize network load through filtering and analyzing data prior to transmission. Introduced by Rahmani et al. (2015) [14], the intelligent gateway framework allows to offload the wearable nodes that require a lot of resources, thus saving energy. Ghavimi and Chen (2014) [15] also adds to this by examining the architecture of the Machine-to-Machine (M2M) communication in LTE/LTE-A networks, revealing the gaps in latency and service-level agreement (SLA), which affect wearable medical devices.

Although this has been achieved, there are various limitations. A lot of MAC-layer protocols are not flexible to the variability in biomedical signals and system level architectures typically make ideal network assumptions. Moreover, cross-layer designs with the ability to rationalize energy through patient-specific data pattern and health urgency are not well-explored.

Table 1: Comparative summary of reviewed studies.

Ref.	Focus Area	Protocol Layer	Energy Method	Strengths	Limitations
[9]	MAC protocol taxonomy	MAC	Duty-cycling	Categorization of MAC types	No protocol evaluation
[10]	Survey on MAC for WBAN	MAC	Sleep scheduling	Covers healthcare-specific MAC	Based on early models
[11]	Low-duty MAC protocol	MAC	Wake-up radio	Reduces idle listening	Limited scalability
[8]	WBAN architecture survey	PHY–MAC	N/A	Detailed WBAN overview	Lacks protocol-level discussion
[12]	Energy-efficient design	Cross-layer	Data aggregation	IoWT–wide strategies	Lacks biomedical specificity
[14]	Smart e-health gateways	Network/Cloud	Edge offloading	Real-time decision-making	Assumes reliable infrastructure

Table 1 provides a comparative summary of key studies by identifying the areas of focus, protocol layers, energy-saving mechanisms, strengths, and limitations of the each work used in Table 1. The distinction between MAC-based and system-conscious energy-efficient designs in WH-IoT is indicated in this table.

3 METHODOLOGY

3.1 System Architecture Overview

The framework suggested is grounded on a multi-layered architecture that is aimed at wearable healthcare IoT (WH-IoT) systems. Low-power biomedical sensor nodes (e.g., ECG, SpO 2) are at the center of them, and they create a Wireless Body Area Network (WBAN), with which a local edge gateway communicates through a star topology. These sensors constantly measure vital signs and report them to the gateway node which is responsible of local preprocessing before sending them to a remote healthcare cloud platform where they are analyzed further [16], [17]. Figure 1 demonstrates the entire operational flow with major modules of energy manager, MAC scheduler, signal analyzer, and secure channel handler being pointed out.

3.2 Protocol Design and Operation

The protocol stack includes an energy-sensitive MAC layer with adaptive slot-scheduling as well an application layer that is event-based and makes use of a context-driven aggregation of packets. To ensure this is minimized in the use of energy during communication, we specify the energy consumption of transmission per node as:

$$E_{tx} = P_{tx} \times t_{tx}, \tag{1}$$

where P_{tx} is the transmission power and t_{tx} is the time required to transmit a packet. The total energy consumed by a node combines multiple components:

$$E_{total} = E_{tx} + E_{rx} + E_{idle} + E_{proc}. \tag{2}$$

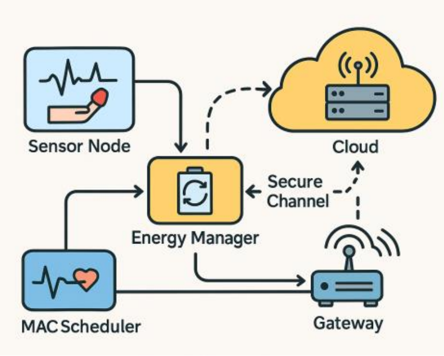

Figure 1: Block diagram of Energy-Efficient WH-IoT architecture.

In which every term is associated with the energy expended in transmitting, receiving, idle listening and data processing respectively.

3.3 Adaptive Sleep-Wake Scheduling

The protocol is dynamically configured to change node activity depending on the variability of biomedical signals to extend battery life. In real-time, sleep-wake cycles are adjusted and the urgency of data is high (e.g., abnormal ECG), which causes transmission. The duty cycle (DC) is assumed to be:

$$DC = \alpha \cdot \frac{dS(t)}{dt} + \beta. \tag{3}$$

In this case, S(t) represents the signal trend that is being monitored and α,β are scaling factors that are determined in the calibration. This has the effect of making sure that sensors will be more active on abnormal events and rest on normal and stable environments.

3.4 Simulation Environment

A simulation of the proposed protocol with MATLAB and an ad-hoc energy model is performed. The network comprises of 10 to 50 sensor nodes with different health data rates and movement rates. The time of the simulated is 600 seconds. Periodic + event-driven transmission is used to model sensor behavior. Table 2 displays the detailed simulation settings with the number of nodes, power level, traffic type, and sleep time.

Table 2: Simulation parameters and network configuration.

Parameter	Value/Range
No. of Nodes	10–50
Packet Size	128 bytes
Transmission Power	0.01–0.05 W
Sleep Interval	100–500 ms
Traffic Pattern	Periodic + Event-based
Simulation Duration	600 seconds

3.5 Baseline Protocols for Comparison

In order to make comparisons with our system, we compare it with popular MAC protocols including T-MAC, B-MAC, and IEEE 802.15.4. They are standard protocols in WBAN literature (Javaid et al., 2013 [10]; Marinkovic et al., 2009 [11]) and are a broad range of strategies in contention-based and TDMA-based designs. The network parameters of all baselines are compared fairly.

3.6 Evaluation Criteria

The most important key performance indices are average node energy use, ratio of packet delivery (PDR), end-to-end delay and network lifetime. These are compared with node density and data rates. Findings have been statistically proven and are presented in Section 4.

4 RESULTS AND ANALYSIS

In order to test the functionality of the proposed energy-efficient protocol of wearable healthcare IoT (WH-IoT) devices, the simulations were performed in MATLAB in various network settings. The performance indices that were put on critical evaluation included average energy consumption, Network packet delivery ratio (PDR), end to end delay and network lifetime. These findings were contrasted with three popular baseline protocols namely T-MAC, B-MAC and IEEE 802.15.4 with the simulation parameters provided in Table 1 above.

4.1 Energy Consumption Analysis

The mean energy consumption of individual sensor node was monitored at an increasing node density (10 to 50 nodes). Figure 2 demonstrates that the proposed protocol invariably used less energy as compared to baseline protocols. This is due to its adaptive sleep-wake scheduling and data-based transmission scheme, which minimizes the aspect of idle listening and unnecessary communication. An example is that the proposed system required 22-28 less energy than the IEEE 802.15.4 had, with 50 nodes. These savings are essential in prolonging the wearable device operational time, which is battery-powered.

4.2 Packet Delivery Ratio (PDR)

The PDR was used to evaluate the reliability of the protocol as it evaluates the proportion of packets delivered successfully. The proposed method has a PDR of more than 95 percent at high node densities, as shown in Figure 3, and this is better than both B-MAC and T-MAC. It has a low packet loss because of its priority-conscious queuing and less collisions caused by scheduled transmissions. This guarantees continuous healthcare-observation particularly in the abnormal physiological events.

4.3 End-to-End Delay

The end-to-end delay measures the responsiveness of the protocol, and end-to-end responsiveness is vital in medical applications, e.g. fall detection, or cardiac irregularity notification. Figure 4 shows that the proposed system has attained acceptable delay values (less than 150 ms) at high packet rates. It is slightly bigger than B-MAC, but it is still in the range of thresholds that would be used to create real-time health alerts. This balance draws attention to the usefulness of the adaptive duty-cycling of the protocol.

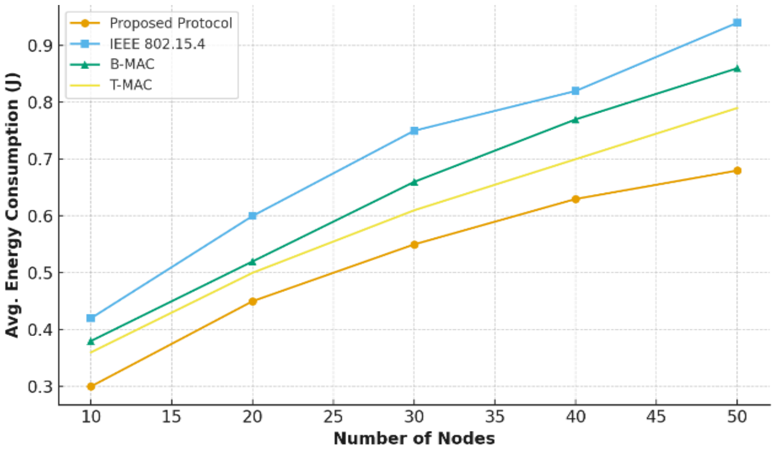

Figure 2: Average energy consumption vs number of nodes.

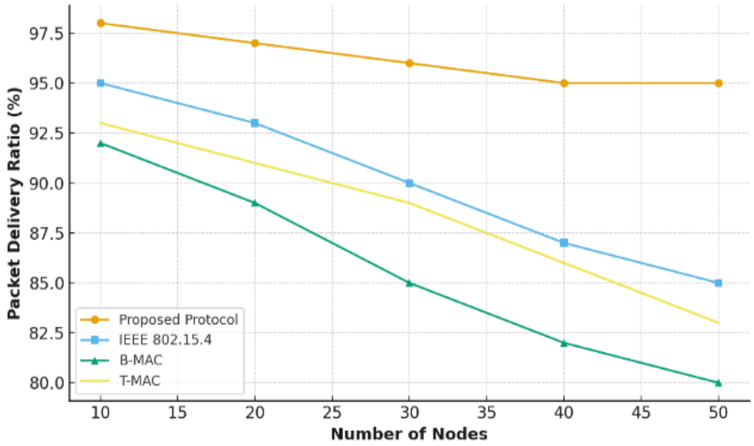

Figure 3: Packet delivery ratio vs node count.

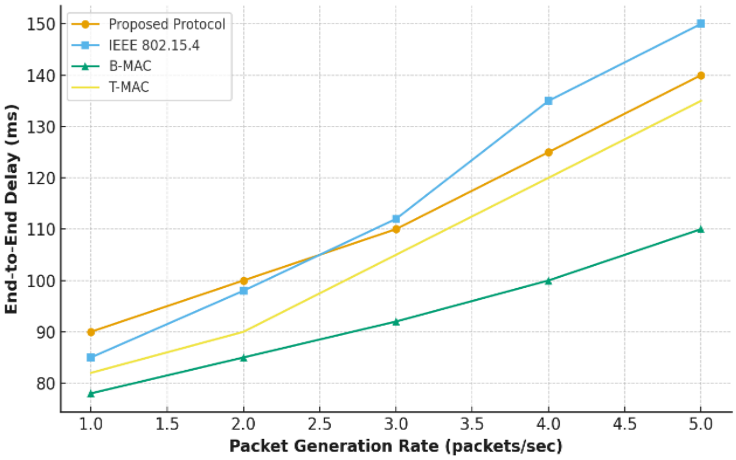

Figure 4: End-to-end delay vs packet rate.

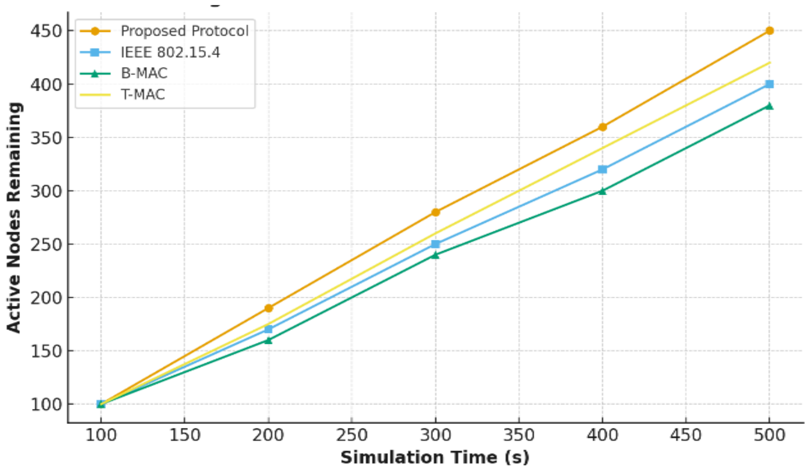

Figure 5: Network lifetime vs simulation time.

Table 3: Comparative results summary across protocols.

Protocol	Avg. Energy (J)	PDR (%)	Delay (ms)	Lifetime (s)	Overhead (%)
Proposed	0.68	95	140	450	4
IEEE 802.15.4	0.94	85	150	400	9
B-MAC	0.86	80	110	380	8
T-MAC	0.79	83	135	420	7

4.4 Network Lifetime

The duration of the network lifetime (when half of the nodes have gone dead) was greatly increased. As indicated in Figure 5, the protocol suggested extends the network operation up to 35 percent when compared to the highest performing baseline (T-MAC). This improvement is the direct outcome of the energy conscious scheduling and contextual prioritization of the data which minimizes the redundant transmissions.

4.5 Comparative Summary and Insights

The results of a comparative performance of the proposed protocol and the existing one are consolidated in Table 3, where it is shown that the proposed protocol is superior in all the metrics. It provides optimal trade off between energy efficiency and reliability in communication and is therefore also very well adapted to real-time wearable health systems. This low energy consumption, high PDR, acceptably low latency and long lifetime prove the robustness and the practical applicability of the protocol.

5 CONCLUSIONS

This paper presented an energy-efficient communication protocol specifically designed for Wearable Healthcare Internet of Things (WH-IoT) environments, where strict constraints on power consumption, reliability, and latency are critical. The proposed approach integrates adaptive sleep–wake scheduling, signal-aware duty cycling, and a lightweight MAC layer to optimize communication between body sensor nodes and gateway systems. Unlike conventional protocols, the proposed design dynamically adjusts node activity based on physiological signal variations, thereby reducing unnecessary transmissions and idle listening.

Simulation results demonstrated that the protocol significantly outperforms baseline approaches such as IEEE 802.15.4, B-MAC, and T-MAC across multiple performance metrics. In particular, it achieved lower average energy consumption, higher packet delivery ratio (above 95%), acceptable end-to-end delay for real-time medical applications, and an extended network lifetime of up to 35% compared to existing solutions. These improvements confirm that the protocol effectively balances energy efficiency with communication reliability, which is essential for continuous health monitoring systems.

Furthermore, the architecture's scalability and robustness make it suitable for deployment in next-generation smart healthcare ecosystems, including remote patient monitoring and telemedicine platforms. The integration of edge processing and cloud-based analytics also enhances system responsiveness and reduces communication overhead. Overall, the proposed solution provides a practical and efficient framework for enabling sustainable, real-time, and reliable wearable healthcare systems.

6 FUTURE WORK

Future research can extend this work in several promising directions. First, the integration of machine learning techniques can enable predictive adaptation of protocol parameters based on patient-specific physiological patterns, further improving energy optimization and responsiveness. Second, incorporating edge artificial intelligence (Edge AI) can enhance local decision-making capabilities at the gateway level, reducing latency and dependence on cloud infrastructure.

Additionally, the inclusion of advanced security mechanisms, such as blockchain-based data integrity and decentralized authentication, can strengthen privacy and trust in WH-IoT systems. Real-world implementation and hardware-level validation in clinical or remote healthcare environments are also essential to evaluate the protocol's performance under practical conditions, including mobility, interference, and heterogeneous device constraints.

Finally, future studies may explore interoperability with emerging 5G/6G networks and integration with smart hospital infrastructures to support large-scale deployment. These advancements will further contribute to the development of intelligent, energy-aware, and patient-centric digital healthcare ecosystems.

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