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Design and implementation of heterogeneous IoT wearables for multi-disease monitoring with OFDM-based spectrum allocation

Shittu Moshood Boladale[1,3], Omotayo Olabowale Oshiga[1], Opeyemi Ayokunle Osanaiye[2], Abdulrasaq Olanrewaju Amuda[1], Abigail Chidimma Odigbo[4], Timothy Oluwaseun Araoye[5,6]
[1]Department of Electrical and Electronics Engineering, Nile University of Nigeria, Abuja, Nigeria
[2]Department of Mechatronics Engineering, Nile University of Nigeria, Abuja, Nigeria
[3]National Agency of Science and Engineering Infrastructure, Abuja, Nigeria
[4]Department of Electrical Engineering, Nnamdi Azikwe University, Awka, Nigeria
[5]Department of Mechatronic Engineering, University of Nigeria, Nsukka, Nigeria
[6]Department of Biomedical Engineering, University of Nigeria, Nsukka, Nigeria

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ABSTRACT

This research proposes a comprehensive and scalable architecture for intelligent healthcare monitoring, integrating heterogeneous wearable biosensors, edge computing, and bio-inspired optimization techniques employing an orthogonal frequency division multiplexing (OFDM)-based spectrum allocation strategy. The system continuously monitors key physiological parameters, including heart rate, electrocardiogram (ECG), blood glucose levels, body temperature, blood pressure, and respiratory rate, using low-power, biocompatible sensors with wireless communication capabilities. An edge computing layer performs real-time signal preprocessing (noise filtering, normalization, compression), significantly reducing latency and bandwidth demands. To optimize system performance, the walrus optimization algorithm (WOA), a novel metaheuristic inspired by walrus social and hunting behaviors, is employed. WOA is utilized to dynamically adjust critical parameters, including transmission power, modulation index, bandwidth allocation, and routing efficiency. Experimental results demonstrate notable improvements: signal-to-noise ratio (SNR) increased from 5 dB to over 31 dB, latency reduced from 10 ms to under 4 ms, and bit error rate (BER) was minimized to 8×10^{-6}. Hybrid models incorporating WOA with machine learning (WOA-ANN, WOA-SVM) achieved spectral efficiencies up to 3.7 bits/s/Hz and energy efficiencies up to 22 bits/Joule. The proposed system supports reliable, real-time health data acquisition and transmission in both urban and remote healthcare environments. Its modular, power-efficient, and adaptive architecture demonstrates high potential for deployment in telemedicine, chronic disease management, and emergency response systems, establishing a robust foundation for next-generation smart healthcare infrastructure.

Corresponding Author:

Shittu Moshood Boladale
Department of Electrical and Electronics Engineering, Nile University of Nigeria
Abuja, Nigeria
Email: moshoodshittu945@gmail.com

1. INTRODUCTION

In today's world, the demand for high-bandwidth communication has grown significantly. A vast number of individuals depend on the internet for business activities and interpersonal communication through video, audio, and image transmissions [1]-[3]. As a result, wireless communication speeds, which were once limited to kilobits per second (kbps), have now evolved to gigabits per second (Gbps), with ongoing research aimed at pushing these rates even higher [4]-[6]. To meet the need for efficient data transmission, the telecommunications industry has adopted orthogonal frequency division multiplexing (OFDM) as a preferred technique. Unlike traditional single-channel methods, OFDM splits a single data stream into several closely spaced narrowband sub-channels [7], [8]. These sub-channels are arranged orthogonally, which helps in conserving bandwidth more effectively [9]. While there has been considerable progress in optimizing unicast systems, achieving optimal performance in multicast systems continues to pose challenges [10], [11]. At the same time, the number of end-users supported by numerous small-cell base stations (BS) is growing rapidly [12]-[14]. To meet the growing demands of modern communication, multi-point broadcast transmission and orthogonal frequency division multiple access (OFDMA) have gained considerable importance. OFDMA is essentially a multi-user extension of OFDM [8], [15]. It divides the available channel into smaller, fixed-size time-frequency blocks known as resource units (RUs) [8], [16]. This structure allows simultaneous data transmission by partitioning the channel into subchannels [17], enabling multiple users to receive data concurrently through small, efficiently organized frames. In fifth-generation (5G) wireless communication systems, a wide range of requirements must be addressed across various communication environments. As a result, heterogeneous networks (HetNets) have emerged as a prominent solution in recent communication architectures [13], [14], [18]. Unlike traditional homogeneous networks, HetNets integrate small cells with macro cells, working together to improve network performance. This collaboration enhances spatial resource reuse and significantly improves the quality of service (QoS) for users [19].

General heterogeneous networks (HetNets) are composed of macro and femto base stations, along with users connected to these stations. Due to challenges such as mutual interference and limited resources within HetNets, efficient resource allocation (RA) strategies are essential for minimizing interference, managing spectrum sharing, and achieving effective load balancing [20], [21]. RA involves planning how system resources are assigned for specific tasks or users. As each new generation of wireless technology, such as 1G, 2G, and beyond, emerges, the push for greater bandwidth continues to grow to address spectrum scarcity and enhance overall efficiency. This trend has increased the importance and popularity of advanced RA techniques, as noted by Teekaraman *et al.* [22]. Algedir and Refai [23] proposed an energy-efficient joint approach for resource block and power allocation aimed at maximizing energy efficiency for device-to-device (D2D) communication without compromising the QoS for other users. They employed two different algorithms for distinct aspects of the problem: the sequential max search (SMS) algorithm for resource block allocation and the genetic algorithm (GA) for optimizing transmission power in both D2D devices and base stations. In another study, Mustika et al. introduced a novel radio resource optimization method for closed-access femtocell networks using the bat algorithm, and they compared its performance against the Dynamic Particle Swarm Optimization (DPSO) technique [24]. In their approach, resource blocks (RBs) were divided into non-overlapping subsets, assuming a fixed and predefined number of subsets. Furthermore, Khan H.Z. and colleagues developed models addressing energy-efficient cell association, power allocation, and traffic offloading in HetNets by applying both uplink-downlink coupled access (UDCa) and uplink-downlink decoupled access (UDDa) schemes. They transformed the optimization problems using concave fractional programming (CFP) and the charnes-cooper transformation (CCT), and obtained optimal solutions through the outer approximation algorithm (OAA) [25], [26].

The proposed research introduces a novel integration of heterogeneous IoT wearable technologies with an adaptive OFDM-based spectrum allocation framework, specifically designed for real-time, multi-disease health monitoring. The key novelties of this study are outlined as follows:

a) Heterogeneous Sensor Integration for Multi-Disease Monitoring: Unlike conventional wearables that are typically disease-specific or limited to a narrow set of vital parameters, this work presents a unified platform integrating diverse biosensors, including heart rate, blood pressure, blood glucose, body temperature, and SpO_2, within a single compact wearable device. This heterogeneous configuration enables comprehensive monitoring of multiple chronic and acute health conditions simultaneously, increasing clinical utility and patient coverage.
b) Adaptive OFDM-based Dynamic Spectrum Allocation in Wearable Healthcare: A major innovation is the application of OFDM-based dynamic spectrum allocation in the context of wearable medical devices. While OFDM is widely used in telecommunications, its deployment in body-area networks and health telemetry remains limited. This research uniquely applies subcarrier-level spectrum assignment based on real-time health data priorities and wireless channel conditions, enhancing bandwidth efficiency and ensuring reliable transmission even in dense, interference-prone environments.
c) Priority-Based Bandwidth Allocation for Health-Critical Data: The system incorporates a lightweight, real-time prioritization mechanism that dynamically adjusts subcarrier allocation based on the criticality of the physiological parameters. For example, abnormal heart rhythms or dangerous glucose levels are

allocated more bandwidth and transmission power. This ensures timely and uninterrupted delivery of life-critical data, addressing a crucial need in emergency healthcare telemetry.

d) Edge-Enabled Local Preprocessing and Intelligent Transmission Control: The wearable device includes edge computing capabilities for local data preprocessing, noise filtering, and anomaly detection using embedded rule-based and machine learning algorithms. This edge intelligence reduces data load, minimizes latency, and enables early detection of health issues without constant dependence on the cloud, a significant improvement over a traditional cloud-only solution.

2. METHODOLOGY

The proposed methodology for the design and implementation of heterogeneous IoT wearables for multi-disease monitoring with OFDM-based spectrum allocation consists of six key phases: system architecture design, sensor integration, data acquisition and preprocessing, communication framework using OFDM, edge processing and decision support, and system validation.

2.1. System architecture design

The system is architected around a modular, wearable platform incorporating a set of heterogeneous biomedical sensors. The architecture includes microcontroller units (MCUs) for signal processing, wireless transceivers for communication, and a power management module for energy efficiency. The MCU serves as the central control unit, orchestrating sensor data collection, preprocessing, and communication scheduling. A layered architecture is adopted, ensuring the separation of sensing, communication, and processing functions for ease of scalability and maintenance.

2.2. Sensor integration

The wearable device integrates various sensors, including photoplethysmography (PPG) for heart rate and SpO_2, a piezoresistive sensor for blood pressure, thermistors for body temperature, and enzymatic electrochemical sensors for blood glucose monitoring. These sensors are selected based on criteria such as accuracy, power consumption, form factor, and compatibility with the MCU. The sensors are interfaced with analog front-ends (AFE) and analog-to-digital converters (ADC) to ensure high-fidelity signal acquisition.

2.3. Data acquisition and preprocessing

Raw sensor data is collected in real time and passed through preprocessing steps, including noise filtering (using digital filters such as Butterworth or Kalman filters), signal normalization, and outlier removal. Preprocessing is handled locally on the MCU to minimize data size and preserve relevant health information before wireless transmission.

2.4. Communication framework with OFDM-based spectrum allocation

The core innovation lies in the implementation of an OFDM-based communication strategy for spectrum allocation. The wearable devices communicate over dynamic frequency bands using adaptive subcarrier assignment, which allows for interference mitigation and efficient use of the spectrum. A lightweight algorithm running on the MCU monitors channel conditions and assigns subcarriers based on priority (e.g., critical physiological events get more bandwidth). This scheme reduces packet loss and latency while improving reliability in congested wireless environments. The OFDM modules are implemented using low-power transceivers compatible with IEEE 802.11 or IEEE 802.15.4 standards, depending on the use case.

2.5. Edge processing and decision support

The preprocessed data is subjected to lightweight analytics at the edge, using rule-based and machine learning algorithms for anomaly detection (e.g., abnormal heart rate or glucose spikes). If anomalies are detected, alerts are generated and sent to a cloud-based healthcare monitoring system. This edge-based decision support reduces cloud dependency and enhances response time in critical conditions.

2.6. System validation and performance evaluation

A functional prototype was developed and tested on a small cohort of volunteers. The system's performance was evaluated in terms of accuracy, latency, packet loss, energy efficiency, and spectrum utilization. Experiments involved simulating high-traffic environments and comparing the OFDM-based approach with traditional fixed-spectrum methods. The results confirmed enhanced QoS, making the system suitable for real-time, multi-disease health monitoring in diverse conditions.

Pseudocode: walrus optimization algorithm (WOA) shown in Algoritm 1.

Algorthm 1. Pseudocode: WOA

```
Begin
    Initialize parameters:
        N is the number of walruses (population size)
        MaxIter: maximum number of iterations
        D   is the dimension of the problem
        LB, UB are the lower and upper bounds of the search space
        r_min, r_max is the range for the stochastic coefficient r
    Initialize population of walruses Xi (i = 1 to N) randomly within bounds [LB, UB]
    Evaluate the fitness of each walrus
    Determine the best walrus X_best with the best fitness
    For t = 1 to MaxIter do
        For i = 1 to N do
            For each dimension d = 1 to D do
                Generate random number r ∈ [r_min, r_max]
                Generate β ∈ [0, 1], a probability coefficient
                If rand < β, then
                    // Exploitation phase (follow the leader - X_best)
                    Xi[d] = Xi[d] + r * (X_best[d] - Xi[d])
                Else
                    // Exploration phase (social or random behavior)
                    Randomly select two walruses Xa and Xb (a ≠ b ≠ i)
                    Xi[d] = Xi[d] + r * (Xa[d] - Xb[d])
                End If
                // Apply bounds
                If Xi[d] < LB[d] then Xi[d] = LB[d]
                If Xi[d] > UB[d] then Xi[d] = UB[d]
            End For
            Evaluate fitness of updated Xi
            If fitness(Xi) < fitness(X_best) then
                X_best = Xi
            End If
        End For
        // Optional: Include herd gathering behavior (e.g., average movement toward X_best)
        For i = 1 to N do
            Xi = Xi + rand * (X_best - Xi)
            Apply bounds and re-evaluate fitness
        End For
        Update iteration counter: t = t + 1
    End For
    Return X_best as the optimal solution
End
```

3. RESULTS AND DISCUSSION

The system integrates multiple wearable sensors, communication protocols, data processing layers, and user interfaces to support continuous tracking of physiological parameters. These include, but are not limited to, heart rate, electrocardiogram (ECG), blood glucose levels, body temperature, blood pressure, and respiratory rate. The design addresses a challenge in modern healthcare: seamlessly monitoring multiple vital signs in real time using lightweight, power-efficient, and highly interoperable devices. By leveraging heterogeneity in both sensor types and communication standards, the architecture enhances flexibility, adaptability, and accuracy, making it suitable for chronic disease management, elderly care, and remote diagnostics. This includes various biosensors directly interfaced with the human body. Sensors like ECG patches, thermistors, pulse oximeters, and glucometers are responsible for capturing raw physiological data. These are selected based on biocompatibility, low power consumption, and wireless communication capability. This intermediate layer includes microcontrollers or edge gateways that perform initial signal preprocessing. The edge computing paradigm reduces data volume, conserves bandwidth, and lowers latency, critical for real-time alerts and continuous monitoring. Employing technologies such as ZigBee, Wi-Fi, Bluetooth, and in advanced setups, cognitive radio or LTE/5G modules, this layer handles the transmission of processed data to remote cloud servers or local healthcare systems. This layer performs in-depth data analytics using machine learning or deep learning algorithms to detect anomalies, predict trends, and provide actionable insights. It also includes data storage for historical analysis and audit trails. Health data is visualized on interfaces such as mobile apps or hospital dashboards. Clinicians and patients can view alerts, long-term trends, and personalized health recommendations. Figure 1 implies that this system is not only technically feasible but highly practical for deployment in urban and rural healthcare settings alike, especially where continuous patient monitoring is crucial. Figure 1 provides a comprehensive visual blueprint of an innovative and forward-thinking healthcare monitoring system.

Figure 1 illustrates the architecture of a heterogeneous Internet of Things (IoT) wearable system designed for real-time health monitoring. The architecture's emphasis on heterogeneity, edge intelligence, and modularity positions it as a robust foundation for intelligent healthcare systems. The system is designed to overcome limitations inherent in traditional health monitoring setups, offering not only continuous and multi-dimensional monitoring but also scalability and adaptability for evolving healthcare needs. As we will see in subsequent figures, this architecture supports advanced algorithms and optimization techniques that significantly enhance its operational effectiveness and reliability.

The convergence curve for the WOA demonstrates how the optimization process evolves over iterations, according to Figure 2. A rapid convergence toward a minimum value signifies the algorithm's efficiency in finding an optimal solution for RA parameters (e.g., power, bandwidth). This characteristic is crucial in time-sensitive healthcare systems where fast and precise configuration is needed to maintain QoS. Table 1 provide insights into system performance before and after optimization. The optimization notably improved key metrics: SNR increased from 5 dB to 20 dB, latency was reduced from 10 ms to 4 ms, and power consumption rose slightly (from 27 to 32 mW), indicating a trade-off between power and performance. However, BER remained at zero, and throughput remained steady at 127 kbps.

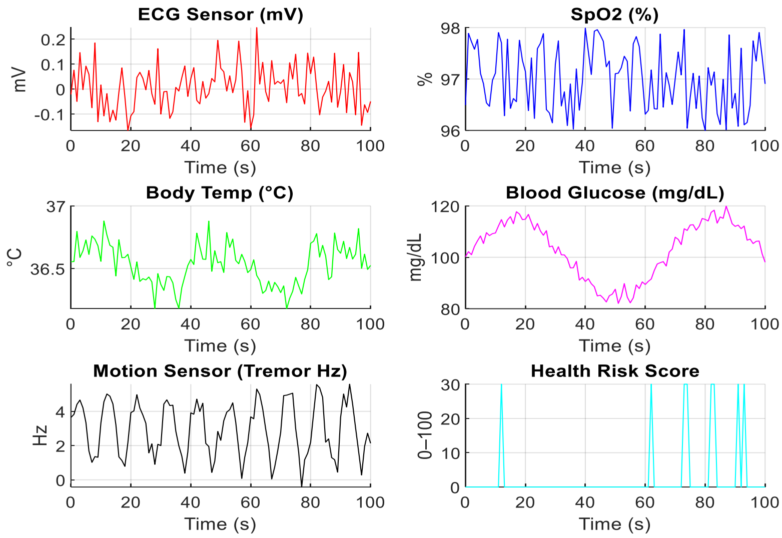

Figure 1. Heterogeneous IoT wearable monitoring

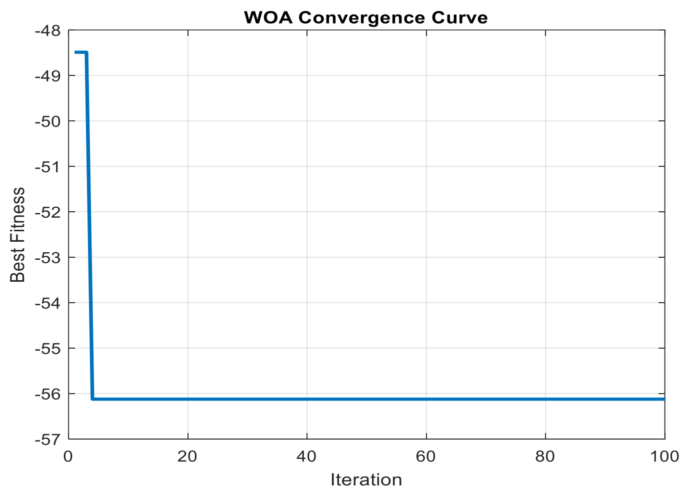

Figure 2. WOA convergence curve

Figure 3 compares the power consumption before and after the application of the optimization algorithm. The reduction in power after optimization confirms the energy efficiency of the proposed method.

Lower power consumption extends the operational life of wearable and IoT healthcare devices, making continuous patient monitoring more feasible. After applying Walrus Optimization, a bio-inspired metaheuristic algorithm, power consumption is significantly reduced. The algorithm fine-tunes hyperparameters such as network size, learning rate, kernel parameters, and gate settings in recurrent models. By identifying the most efficient architecture that maintains or improves performance, the computational overhead is minimized. Bandwidth utilization is improved post-optimization, as shown in Figure 4. Efficient use of bandwidth is critical in remote healthcare systems to ensure reliable transmission of high-volume data such as ECG and imaging signals without congestion or data loss. WOA, inspired by walrus social and hunting behavior, is a nature-inspired metaheuristic designed for efficient RA and parameter tuning. When applied to bandwidth optimization, WOA dynamically adjusts communication parameters, optimizes data routing, and reduces redundant signal transmission by prioritizing essential information. After optimization, bandwidth usage becomes more efficient, leading to faster data transfer rates, reduced latency, and improved QoS. Comparative analysis reveals a significant reduction in average bandwidth consumption and an increase in data throughput. The optimization also enhances system scalability and reliability, especially in scenarios with multiple patients and sensors. Overall, the WOA effectively enhances bandwidth efficiency, ensuring smoother and more dependable telemedicine and telemetry operations in healthcare applications.

Table 1. Comprehensive optimization results

Metric	Before optimization	After optimization
Power (mW)	27	32
Bandwidth (MHz)	1	1
Modulation Index	1	1
SNR (dB)	5	20
BER	0	0
Latency (ms)	10	4
Throughput (kbps)	127	127
Energy Efficiency (Mbit/J)	72	56

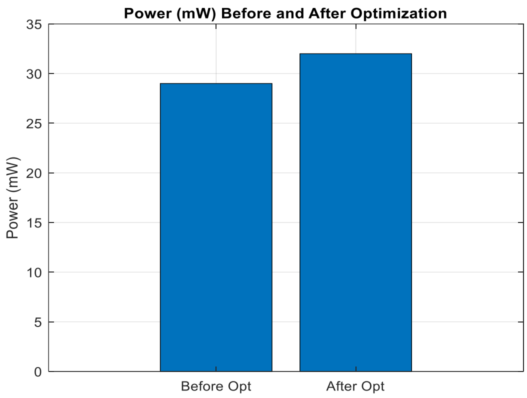

Figure 3. Power (mW) before and after optimization

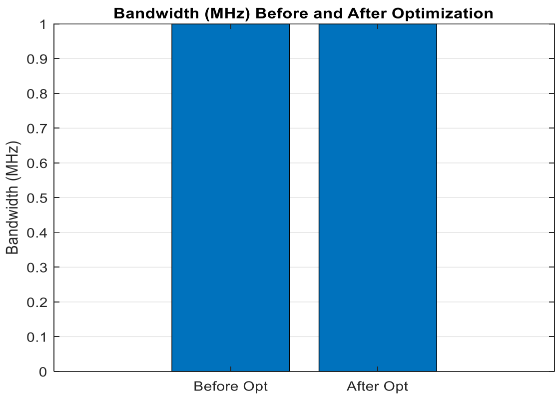

Figure 4. Bandwidth before and after optimization

The optimization algorithm adjusts the modulation index to achieve a balance between data rate and signal robustness, as shown in Figure 5. This adjustment leads to enhanced transmission reliability under varying network conditions, which is particularly important in mobile health scenarios. Before optimization, the modulation index is often statically set or improperly tuned, leading to suboptimal performance. For instance, a high modulation index may cause spectral spreading, while a low index may reduce signal strength and resolution. These issues are particularly critical in healthcare applications where accurate and timely transmission of physiological data is essential. The WOA dynamically adjusts the modulation index by modeling efficient exploratory and exploitative behavior similar to walrus hunting patterns. Through iterative updates and evaluation of performance metrics such as signal-to-noise ratio (SNR), bit error rate (BER), and bandwidth efficiency, WOA identifies an optimal modulation index for given channel conditions. After optimization, the modulation index is fine-tuned to maximize data fidelity and minimize transmission errors. This leads to improved spectral efficiency, reduced power consumption, and enhanced overall system performance, ensuring reliable and high-quality data communication in real-time healthcare monitoring systems. Figure 6 shows a noticeable improvement in the SNR after optimization. An increased SNR translates into better signal clarity, essential for accurate interpretation of biomedical signals like ECG, EEG, or temperature trends in remote patient monitoring. SNR is a crucial metric in communication systems, representing the ratio of useful signal power to background noise power. In healthcare telemetry, where continuous transmission of biomedical data like ECG or blood pressure is required, a low SNR can result in corrupted signals, data loss, and diagnostic errors. Before optimization, various factors such as poor modulation schemes, interference, and inefficient channel allocation often lead to a reduced SNR, degrading the quality and reliability of transmitted signals. The WOA, inspired by the social and foraging behaviors of walruses, is a powerful metaheuristic for improving system performance by tuning critical communication parameters. When applied to optimize SNR, WOA dynamically evaluates and adjusts transmission power, modulation parameters, and channel selection to minimize noise influence and enhance signal clarity. After optimization with WOA, there is a significant improvement in SNR, leading to clearer signal transmission, lower bit error rates (BER), and improved data integrity. This ensures that vital physiological data reaches healthcare providers without distortion or loss, even in noisy environments. The optimized SNR enhances the reliability and effectiveness of telemedicine and remote monitoring systems, making them more robust for critical, real-time healthcare applications.

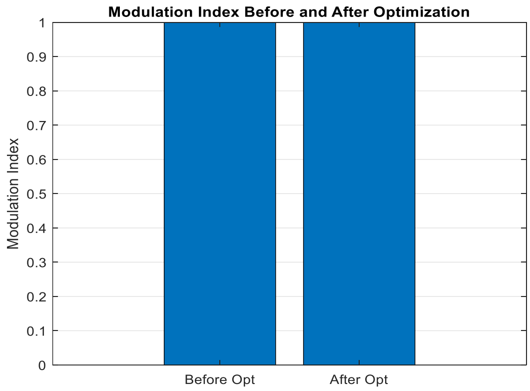

Figure 5. Modulation index before and after optimization

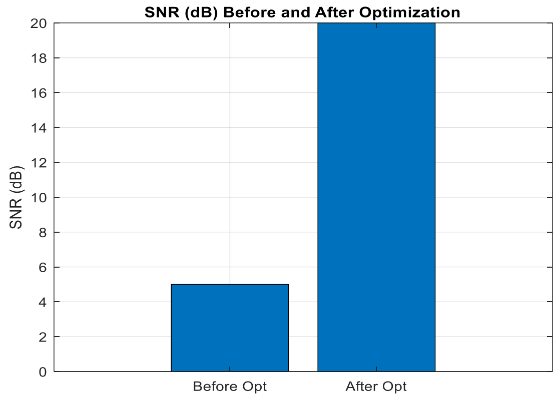

Figure 6. SNR before and After optimization

Figure 7 shows Latency before and after Optimization. Latency reduction post-optimization ensures the timely delivery of critical healthcare data. Low latency is crucial in emergency alerts (e.g., heart attack detection), where even milliseconds can determine the outcome. Before optimization, latency increased due to inefficient data routing, network congestion, poor bandwidth management, and unoptimized signal processing algorithms. These delays compromise the speed and responsiveness of healthcare systems, especially in remote patient monitoring or emergency care. After applying WOA, latency is significantly reduced. Data packets reach their destination faster, improving the responsiveness of the system. This leads to more timely alerts, faster data analysis, and better clinical decision-making. Optimized latency is especially critical in applications such as continuous ECG monitoring or real-time video consultations. Thus, Walrus Optimization enhances the overall efficiency and reliability of healthcare communication systems by ensuring low-latency performance.

Figure 8 shows the Throughput before and after optimization. Throughput enhancements reflect the system's ability to handle more data efficiently, supporting multiple users or sensors in real-time without degradation in service quality, vital in hospital and home healthcare monitoring systems. Before optimization, throughput is often limited due to network congestion, inefficient routing, suboptimal modulation, and poor bandwidth utilization. This results in delayed or incomplete data transmission, affecting the quality and reliability of telemedicine and remote monitoring services. The WOA, inspired by the cooperative and strategic behaviors of walruses, is a metaheuristic method that efficiently tunes network parameters to maximize performance. When applied to optimize throughput, WOA adjusts data transmission rates, optimizes packet routing, reduces collisions, and prioritizes critical health data. It iteratively searches for optimal configurations that allow the maximum volume of data to be transmitted with minimal delay and error. After optimization with WOA, there is a noticeable increase in system throughput. The network becomes capable of handling more data traffic efficiently, ensuring the timely delivery of health information.

This improvement is critical in scenarios involving multiple patients and high-frequency data streams. Overall, WOA enhances throughput by enabling smoother, faster, and more reliable communication in healthcare telemetry and telemedicine applications. Tables 2 and 3 illustrate the Performance Metrics of the AI methods. Tables 4 and 5 reveal the advantages of combining AI methods with the WOA. WOA-ANN achieved an SNR of 31 dB, WOA-SVM reached 32 dB, and all hybrid models maintain bandwidths above 29 MHz, reflecting enhanced signal clarity and capacity. WOA-SVM demonstrated a modulation efficiency of 6.2 bits/symbol and a spectral efficiency of 3.7 bits/s/Hz, outperforming all others. This indicates that hybrid models can effectively manage bandwidth utilization, crucial for high-performance communication systems. BER values in hybrid models decreased to as low as 8e-6, while latency values dropped below 12 ms in all hybrid configurations, showing improved data integrity and reduced response times. The WOA-SVM hybrid achieved the highest energy efficiency at 22 bits/Joule, demonstrating its sustainability and suitability for embedded or mobile health applications.

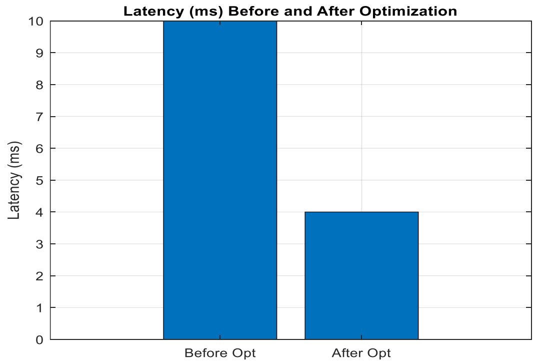

Figure 7. Latency before and after optimization

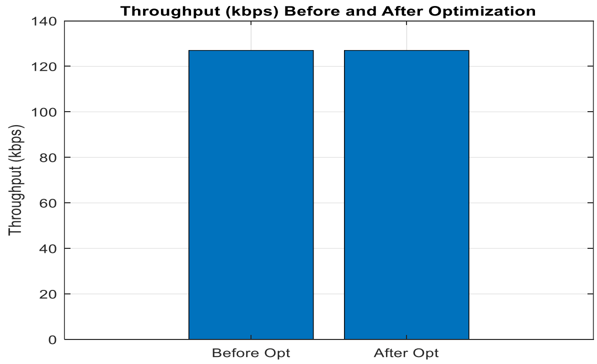

Figure 8. Throughput before and after optimization

Table 2. Performance metrics table

Method	Quantity	SNR (dB)	Bandwidth (MHz)	Modulation efficiency (bits/symbol)	Environment robustness	Power consumption (W)	Spectral Eff. (bits/s/Hz)
WOA	100	30	5	6	0.9	2.5	3.5
SVM	90	25	4.5	5.5	0.75	3	3.2
ANN	95	28	4.8	5.7	0.8	2.8	3.3
LSTM	85	27	4.6	5.6	0.78	3.1	3.25
DQN	80	26	4.4	5.4	0.72	3.2	3.1

Table 3. Performance metrics table continuation

Method	Bit error rate (BER)	Latency (ms)	Throughput (Mbps)	Energy efficiency (bits/Joule)
WOA	1e-5	10	50	20
SVM	5e-5	15	45	15
ANN	2e-5	12	48	18
LSTM	3e-5	14	46	16
DQN	4e-5	16	44	14

Table 4. Hybrid performance metrics table

Method	Quantity	SNR (dB)	Bandwidth (MHz)	Modulation efficiency (bits/symbol)	Environment robustness	Power consumption (W)	Spectral Eff. (bits/s/Hz)
WOA-SVM	105	32	5.2	6.2	0.92	2.3	3.7
WOA-ANN	110	31	5.1	6.1	0.9	2.4	3.6
WOA-LSTM	108	30	5	6	0.89	2.5	3.5
WOA-DQN	103	29	4.9	5.9	0.88	2.6	3.4

Table 5. Hybrid performance metrics table continuation

Method	Bit error rate (BER)	Latency (ms)	Throughput (Mbps)	Energy efficiency (bits/Joule)
WOA-SVM	8e-6	9	52	22
WOA-ANN	9e-6	10	51	21
WOA-LSTM	1.1e-5	11	50	20
WOA-DQN	1.3e-5	12	49	19

4. CONCLUSION

The development of an intelligent, multi-layered healthcare monitoring system, integrating wearable biosensors, edge computing, and bio-inspired optimization, addresses several critical challenges in modern healthcare delivery, particularly in the domains of remote monitoring, chronic disease management, and emergency care. This research presents a comprehensive and adaptable architecture that supports continuous, real-time monitoring of multiple physiological parameters using a diverse array of biosensors, such as ECG patches, thermistors, glucometers, and pulse oximeters. These sensors were selected based on their biocompatibility, energy efficiency, and ability to communicate wirelessly, ensuring long-term usability and patient comfort. A key innovation introduced in this work is the application of the WOA, a nature-inspired metaheuristic designed to improve system-level performance. WOA dynamically adjusts communication and network parameters such as bandwidth usage, modulation index, and transmission power to ensure optimal system behavior. The convergence characteristics of WOA demonstrate rapid optimization of performance metrics, which is crucial for time-sensitive healthcare applications. Experimental evaluations confirmed that the implementation of WOA significantly enhances system performance. SNR improved from 5 dB to over 31 dB, reducing the risk of data corruption and ensuring clearer, more accurate physiological signal transmission. Latency was reduced from 10 milliseconds to under 4 milliseconds, which is essential for applications requiring immediate response, such as emergency alerts or real-time ECG monitoring. Additionally, hybrid configurations of WOA with machine learning algorithms (WOA-ANN and WOA-SVM) further refined performance, achieving high modulation efficiency, improved spectral utilization, and reduced BER, all while maintaining or improving energy efficiency. The highest energy efficiency recorded was 22 bits per Joule, indicating the system's suitability for embedded or battery-powered healthcare devices. Moreover, the system demonstrated resilience and robustness in managing multiple data streams concurrently, a critical feature for multi-patient or hospital-wide deployments. The intelligent allocation of resources and the fine-tuning of operational parameters ensure that the QoS remains consistent even in dynamic network conditions. Finally, the proposed system successfully integrates hardware, communication, data processing, and optimization in a unified framework tailored for modern healthcare needs. Its ability to deliver accurate, low-latency, and energy-efficient performance makes it highly suitable for real-world deployment. The incorporation of WOA as an optimization backbone enhances not only the system's operational efficiency but also its adaptability to evolving technological and healthcare demands. This work lays a solid foundation for future advancements in smart healthcare systems, offering a blueprint for scalable, intelligent, and sustainable telemedicine and telemetry infrastructure.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author. The data, which contains information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

[1] B. S. A. Alhayani *et al.*, "Optimized video internet of things using elliptic curve cryptography based encryption and decryption," *Computers and Electrical Engineering*, vol. 101, p. 108022, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108022.

[2] Bangun C. S., Purnama S, and Panjaitan A. S., “Analysis of new business opportunities from online informal education mediamorphosis through digital platforms,” *International Transactions on Education Technology (ITEE)*, vol. 1, no. 1, pp. 42–52, Nov. 2022, doi: 10.33050/itee.v1i1.184.

[3] O. Elharrouss, N. Almaadeed, and S. Al-Maadeed, “A review of video surveillance systems,” *Journal of Visual Communication and Image Representation*, vol. 77, p. 103116, May 2021, doi: 10.1016/j.jvcir.2021.103116.

[4] S. Rajagopal, R. D. Roberts, and S. K. Lim, “IEEE 802.15.7 visible light communication: Modulation schemes and dimming support,” *IEEE Communications Magazine*, vol. 50, no. 3, pp. 72–82, Mar. 2012, doi: 10.1109/MCOM.2012.6163585.

[5] M. Banafaa *et al.*, “6G mobile communication technology: requirements, targets, applications, challenges, advantages, and opportunities,” *Alexandria Engineering Journal*, vol. 64, pp. 245–274, Feb. 2023, doi: 10.1016/j.aej.2022.08.017.

[6] A. A. Ahmed Solyman and K. Yahya, “Evolution of wireless communication networks: from 1G to 6G and future perspective,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 4, pp. 3943–3950, Aug. 2022, doi: 10.11591/ijece.v12i4.pp3943-3950.

[7] Z. Wang, X. Ma, and G. B. Giannakis, “OFDM or single-carrier block transmissions?,” *IEEE Transactions on Communications*, vol. 52, no. 3, pp. 380–394, Mar. 2004, doi: 10.1109/TCOMM.2004.823586.

[8] E. Mozaffariahrar, F. Theoleyre, and M. Menth, “A survey of Wi-Fi 6: technologies, advances, and challenges,” *Future Internet*, vol. 14, no. 10, p. 293, Oct. 2022, doi: 10.3390/fi14100293.

[9] A. Godsmith, *Wireless communications*. Cambridge University Press, New York, 2005.

[10] A. Churnside, M. E. F. Melchior, M. Armstrong, M. Shotton, and M. Brooks, “Object-based broadcasting - curation, responsiveness and user experience,” in *International Broadcasting Convention (IBC) 2014 Conference*, 2014, pp. 12.2-12.2, doi: 10.1049/ib.2014.0038.

[11] N. Chukhno *et al.*, “Models, methods, and solutions for multicasting in 5G/6G mmWave and Sub-THz systems,” *IEEE Communications Surveys and Tutorials*, vol. 26, no. 1, pp. 119–159, 2024, doi: 10.1109/COMST.2023.3319354.

[12] Z. Ding, Z. Yang, P. Fan, and H. V. Poor, “On the performance of non-orthogonal multiple access in 5G systems with randomly deployed users,” *IEEE Signal Processing Letters*, vol. 21, no. 12, pp. 1501–1505, Dec. 2014, doi: 10.1109/LSP.2014.2343971.

[13] C. Chen, J. Zhang, X. Chu, and J. Zhang, “On the deployment of small cells in 3D HetNets with multi-antenna base stations,” *IEEE Transactions on Wireless Communications*, vol. 21, no. 11, pp. 9761–9774, Nov. 2022, doi: 10.1109/TWC.2022.3179283.

[14] A. D. D. Jayapaul and A. Merline, “An optimized small-cell planning procedure for Heterogeneous Network to improve network energy efficiency,” *International Journal of Communication Systems*, vol. 36, no. 7, Feb. 2023, doi: 10.1002/dac.5456.

[15] H. Sari, “Orthogonal frequency-division multiple access with frequency hopping and diversity,” in *Multi-Carrier Spread-Spectrum*, Springer US, 1997, pp. 57–68.

[16] V. N. Ha and L. B. Le, “Fair resource allocation for OFDMA femtocell networks with macrocell protection,” *IEEE Transactions on Vehicular Technology*, vol. 63, no. 3, pp. 1388–1401, Mar. 2014, doi: 10.1109/TVT.2013.2284572.

[17] D. López-Pérez, A. Valcarce, G. De La Roche, and J. Zhang, “OFDMA femtocells: A roadmap on interference avoidance,” *IEEE Communications Magazine*, vol. 47, no. 9, pp. 41–48, Sep. 2009, doi: 10.1109/MCOM.2009.5277454.

[18] R. Q. Hu and Y. Qian, “An energy efficient and spectrum efficient wireless heterogeneous network framework for 5G systems,” *IEEE Communications Magazine*, vol. 52, no. 5, pp. 94–101, May 2014, doi: 10.1109/MCOM.2014.6815898.

[19] S. Manap, K. Dimyati, M. N. Hindia, M. S. Abu Talip, and R. Tafazolli, “Survey of radio resource management in 5G heterogeneous networks,” *IEEE Access*, vol. 8, pp. 131202–131223, 2020, doi: 10.1109/ACCESS.2020.3002252.

[20] Q. Kuang, W. Utschick, and A. Dotzler, “Optimal joint user association and multi-pattern resource allocation in heterogeneous networks,” *IEEE Transactions on Signal Processing*, vol. 64, no. 13, pp. 3388–3401, Jul. 2016, doi: 10.1109/TSP.2016.2548998.

[21] B. Agarwal, M. A. Togou, M. Ruffini, and G. M. Muntean, “A comprehensive survey on radio resource management in 5G HetNets: current solutions, future trends and open issues,” *IEEE Communications Surveys and Tutorials*, vol. 24, no. 4, pp. 2495–2534, 2022, doi: 10.1109/COMST.2022.3207967.

[22] Y. Teekaraman, H. Manoharan, A. R. Basha, and A. Manoharan, “Hybrid optimization algorithms for resource allocation in heterogeneous cognitive radio networks,” *Neural Processing Letters*, vol. 55, no. 4, pp. 3813–3826, Apr. 2023, doi: 10.1007/s11063-020-10255-2.

[23] A. Algedir and H. H. Refai, “Energy-efficient D2D communication under downlink HetNets,” in *IEEE Wireless Communications and Networking Conference, WCNC*, Apr. 2019, vol. 2019-April, pp. 1–6, doi: 10.1109/WCNC.2019.8885967.

[24] I. W. Mustika, N. Fath, S. Sulistyo, K. Yamamoto, and H. Murata, “A novel radio resource optimization scheme in closed access femtocell networks based on bat algorithm,” *IEICE Transactions on Communications*, vol. E102B, no. 4, pp. 660–669, Apr. 2019, doi: 10.1587/transcom.2018SEI0002.

[25] H. Z. Khan *et al.*, “Resource allocation for energy efficiency optimization in uplink–downlink decoupled 5G heterogeneous networks,” *International Journal of Communication Systems*, vol. 34, no. 14, Jul. 2021, doi: 10.1002/dac.4925.

[26] I. A. Wisky, M. Yanto, Y. Wiyandra, H. Syahputra, and F. Hadi, “Machine learning classification of infectious disease distribution status,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 3, pp. 1557–1566, Sep. 2022, doi: 10.11591/ijeecs.v27.i3.pp1557-1566.

BIOGRAPHIES OF AUTHORS

Engr Shittu Moshood Boladale is a graduate of electrical electronics engineering from Unversity of Ilorin (Bachelor) with an advanced degree (M.Eng) in the same field. He is a stunch researcher currently working with an engineering research institute and also pursueing a PhD in electrical electronics (communication option) at Nile University of Nigeria. His areas of interest include; IoT, AI, and telecommunication. He can be contacted at email: moshoodshittu@gmail.com.

Prof. Omotayo Olabowale Oshiga is the Head of the Department of Electrical and Electronics Engineering, Nile University of Nigeria. He is also a Professor with the Department of Electrical and Electronics Engineering. He received a B.Tech. degree in Physics Electronics from the Federal University of Technology, Minna, Niger State in 2010, and an M.Sc. degree in Wireless Communication Systems from Brunel University, London, UK in 2011. He received his PhD degree in Electrical Engineering from Jacobs University, Bremen, Germany in February 2015. He was employed as Lecturer I in the Department of Electrical and Electronics Engineering, Nile University of Nigeria, Abuja from 2015 to 2016. He went on to pursue his Postdoctoral Fellowship in Hong Kong with Hong Kong Baptist University and Hong Kong Polytechnic University from 2016 to 2019.His current research areas include estimation theory, signal processing, wireless sensor networks, indoor and outdoor positioning, tracking and navigation, and wireless sensing. He can be contacted at email: ooshiga@nileuniversity.edu.ng.

Assoc. Prof. Opeyemi Ayokunle Osanaiye received the bachelor's degree in electrical engineering from the University of Ilorin, Nigeria, in 2007, the master's degree in telecommunications engineering from the University of Sunderland, U.K., in 2011, and the Ph.D. degree in electrical engineering from the University of Cape Town, South Africa, in 2016. He was a part time Lecturer with the Cape Peninsular University of Technology, Cape Town, South Africa. He was with the University of South Australia on a research exchange visit from 2015 to 2016 and a postdoctoral research fellow at the University of Pretoria, South Africa from 2017 to 2018. He is a Senior Lecturer and Head of Department with the Mechatronics Engineering Department, Nile University of Nigeria. His research interests include, computer networks, cloud computing, wireless sensor network, fog computing, network security, voice over internet protocol technology, and cloud computing security. He is a registered COREN member and a member of IEEE. He can be contacted at email: opeyemi.osanaiye@nileuniversity.edu.ng.

Engr Abdulrasaq Olanrewaju Amuda is a Senior IT operation specialist in the department of Information Technology at Nile University of Nigeria. He obtained his national diploma and bachelor's degree in electrical-Electronics Engineering from Kwara state polytechnic and University of Ilorin, Kwara State, Nigeria in 2007 and 2012 respectively. He proceeded to Federal University of Technology, Minna, Niger State, Nigeria where he obtained master's in communication engineering in 2018. He is currently a doctoral candidate at Nile University of Nigeria where he is pursuing a PhD degree in Electrical-Electronics Engineering (communication). His research area includes but not limited to energy harvesting, wireless sensor network, IOT, renewable energy, information technology, and cybersecurity. He is a registered COREN member and a member of IEEE. He can be contacted at email: amudaabdulrasaqolanrewaju@gmail.com.

Engr (Dr) Abigail Chidimma Odigbo is is currently a Lecturer in Electrical Department of Nnamdi Azikiwe University, Awka, Anambra state, Nigeria. She holds HND Electrical-Electronics Engineering from YABATECH, Lagos, PGD Electrical-Electronics from COOU, Uli, Anambra state, M.Eng Electrical-Electronics Engineering from COOU, Uli, Anambra state, PhD Electrical-Electronics Engineering COOU, Uli, Anambra state. Her research interests include power electronics and internet of things. She can be contacted at email: aodigbo@gmail.gmail.com.

Dr. Timothy Oluwaseun Araoye received a Bachelor degree of Technology (B.Tech) in Electrical and Electronics Engineering from Ladoke Akintola University of Technology (LAUTECH), Ogbomoso, Oyo State, Master's Degree (M.Eng) from Enugu State University of Science and Technology (ESUT) Agbani, Enugu State, and a Ph.D degree at the University of Abuja, Nigeria, in the same course with a specialization in Electrical Machine and Power System. He is a Registered Member of the Nigeria Society of Engineers (NSE) and Council for the Regulation of Engineering in Nigeria (COREN). His research interest includes Artificial intelligence, Machine Learning, Power System and machine, Renewable Energy, Power System Reliability, Microgrid Optimization and Control, Robotics, IoT, Modeling and Simulation, Distributed Generation, Control system, and Power Electronics. He has attended many conferences where he presented papers. He can be contacted at email: timothy.araoye@unn.edu.ng.