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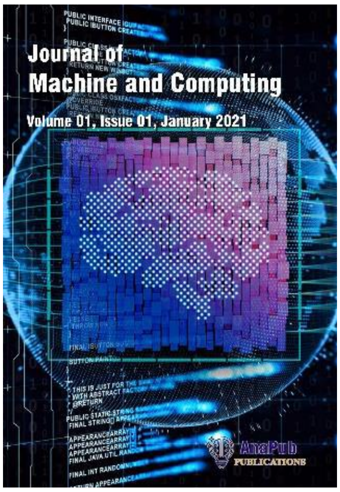

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DOI: 10.53759/7669/jmc202505150

Reference: JMC202505150

Journal: Journal of Machine and Computing.

Received 02 February 2025

Revised from 29 April 2025

Accepted 19 June 2025

Please cite this article as: Devikala S, Menaka D, Ashok kumar L and Ravichandran D, "Optimized Medical Data Transmission Using OFDM-VLC and Reinforcement Learning in Remote Health Monitoring", Journal of Machine and Computing. (2025). Doi: https://doi.org/10.53759/7669/jmc202505150.

Optimized Medical Data Transmission Using OFDM-VLC and Reinforcement Learning in Remote Health Monitoring

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Abstract

In remote healthcare systems, the efficient, secure, and real-time transmission of biomedical signals such as ECG is critical. Traditional RF-based communication often suffers from interference, limited bandwidth, and security concerns. Visible Light Communication (VLC), particularly when combined with Orthogonal Frequency Division Multiplexing (OFDM), presents a promising alternative due to its high bandwidth, electromagnetic immunity, and inherent data security. However, VLC systems are highly sensitive to environmental dynamics like ambient light variation and patient movement, limiting their reliability. Previous research has explored AI-assisted VLC systems and modulation schemes, yet many suffer from static configurations, limited adaptability, high energy consumption, and lack of real-time optimization. This work introduces a novel Q-learning-optimized OFDM-VLC system tailored for remote health monitoring. The system leverages reinforcement learning to dynamically adjust modulation schemes, transmission power, and encoding strategies in response to environmental conditions (e.g., SNR, ambient light, mobility), enabling energy-efficient and error-resilient data transfer. Using the MIT-BIH Arrhythmia dataset, ECG signals are preprocessed, digitized, modulated using adaptive QPSK or 16-QAM, and transmitted over a VLC channel. A Q-learning agent selects optimal actions in real time to minimize BER and energy use while maximizing throughput and SNR. MATLAB was employed for system design, simulation, and performance evaluation. Compared to static systems, the proposed method reduced BER from 0.078 to 0.015, improved SNR from 21.3 dB to 29.8 dB, increased throughput from 16.7 kbps to 22.4 kbps, and lowered latency from 14.6 ms to 9.0 ms. Energy consumption dropped from 1.35 J/bit to 0.89 J/bit, and ECG reconstruction accuracy rose from 85.3% to 96.7%. The integration of reinforcement learning with VLC-OFDM significantly enhances the reliability, efficiency, and adaptability of real-time biomedical data transmission in remote health monitoring.

Keywords: VLC, OFDM, Q-learning, Remote Health Monitoring, Reinforcement Learning

1. Introduction

The increase in chronic diseases and the necessity for ongoing monitoring of patients have accelerated the evolution of remote health monitoring systems [1]. Conventional communication technologies based predominantly on radio frequency technologies are severely constrained in healthcare applications [2]. These include limited bandwidth, vulnerability to electromagnetic interference, and possible security risks, especially where confidentiality and integrity of medical information are paramount [3]. VLC, however, has emerged as an appealing alternative, with benefits of high data rate, immunity to RF interference, and intrinsic security advantages [4]. Such properties render VLC very versatile for hospital and home health care healthcare applications [5]. VLC system development has also been made feasible by the integration of Orthogonal Frequency Division Multiplexing (OFDM), which facilitates improved spectral efficiency and multi-channel, high-speed data transmission [6]. Even as such advantages are realized, VLC systems are very sensitive to environmental scenarios such as variations in ambient light, device mobility, and signal loss, which have adverse effects on transmission performance [7]. Static system configurations are typically unsuitable to such variability, leading to compromised quality of service, including high bit error rates (BER), low signal-to-noise ratios (SNR), and high energy consumption [8].

To address such challenges, recent research has focused on the incorporation of machine learning techniques into communication systems. Reinforcement learning (RL) more particularly, Q-learning, is a viable option by enabling adaptive system modification with environmental feedback [9]. Unlike traditional algorithms, Q-learning learns optimal policies via extensive exploration of the environment without the necessity for pre-defined system models [10]. This study puts forward a Q-learning-enhanced OFDM-VLC system for remote transfer of medical data that can improve flexibility, reduce errors, and maximize energy efficiency under fluctuating healthcare conditions.

1.1 Research Gap

Despite the advancements in VLC and AI-aided adaptive modulation for medical data transmission optimizing high-speed, real-time, and secure data transmission in dynamic health environments is still a challenge. Most of the existing research is devoid of end-to-end solutions combining energy-efficient modulation, multi-channel transmission, and efficient reinforcement learning for remote health monitoring [11], [12]. Privacy-preservation schemes and optimized physical layer algorithms are also not well-explored [13]. Therefore, the requirement is to carry out extensive research using OFDM-VLC with reinforcement learning to enhance medical data transmission efficiency, security, and flexibility in remote health monitoring systems.

1.2 Research Motivation

The motivation for this work arises from the growing need for secure, real-time, and dependable data transfer in medical remote monitoring systems. RF communication is not dependable in medical environments, while VLC offers a secure, interference-free solution. However, its performance is hindered by environmental dynamics. The incorporation of reinforcement learning offers an intelligent solution, where adaptive tuning of transmission parameters is enabled to optimize for high-quality, energy-efficient, and dependable transfer of medical data.

1.3 Research Significance

This research is of vital value in remote healthcare technology development with the combination of reinforcement learning and VLC-based OFDM. It addresses important issues of signal attenuation, energy inefficiency, and latency in real-time systems. With smart adjustment of communication parameters, the system enhances the efficiency and reliability of medical data transmission. This results in more secure, quicker, and more scalable medical IoT applications, which are of great value in real-time and efficient patient monitoring.

1.4 Key Contributions

- Designed a Visible Light Communication system using Orthogonal Frequency Division Multiplexing to support high-speed medical data transmission.
- Applied a reinforcement learning (Q-learning) algorithm to dynamically optimize transmission parameters like power levels, subcarrier allocation, and modulation schemes.
- Enabled real-time adaptation to changing conditions such as ambient light and device mobility, improving system reliability.
- Achieved lower bit error rate, improved signal-to-noise ratio, reduced energy consumption, and better throughput compared to static systems.
- Simulated the system using MATLAB and evaluated it using real biomedical datasets (e.g., MIT-BIH, MIMIC-IV) for practical health monitoring scenarios.

1.5 Rest of Section

In Section 2 literature review is provided, section 3 proposed method working is given. In section 4 findings and analysis and section 5 conclusion and further studies.

2. Related Works

Li et al. [14] proposed ADDETECTOR, an IoT device-based privacy-preserving Alzheimer's detection system with topic-based linguistic features, federated learning, and differential privacy in a three-layer framework. The system collects audio data from smart home IoT devices for enhancing detection with data confidentiality via an asynchronous privacy-preserving aggregation framework. The system was evaluated on 1010 trials with 81.9% accuracy and 0.7-second time overhead. The paper, however, presumes that attackers do not possess any access to IoT device data, which may limit practical security resilience. Future work includes exploring better features and experiments on larger datasets. Similarly, Salem et al., [13] suggested a secure scheme for Internet of Medical Things (IoMT) to respond against Man-in-the-Middle (MitM) attacks that can replay typical data in emergency situations. The technique employs signal strength-based keys and sends a small signature along with a message authentication code in order to maintain privacy and minimize energy consumption. Results indicate accurate detection of emergencies with a very low rate of false alarms at 3%. But the research does not consider jamming attacks or dynamic channel threats. Future research intends to investigate channel hopping with authentication keys as seeds for enhanced resilience.

Kavitha et al. [15] investigated VLC for indoor transmission of medical data using LEDs, with the incorporation of Wireless Sensor Networks (WSNs) to collect patient data. They suggested a Cluster Nodes Reinforcement Scheme (CNRS) to improve routing efficiency and network lifetime. The scheme involves Binary Phase Shift Keying (BPSK) in conjunction with DC-biased Optical OFDM (DCO-OFDM) to analyze Bit Error Rate (BER) and End-to-End (ETE) delay. Outcomes showed enhanced VLC-based data transmission performance. The experiment is deficient in real-time proof and does not cover external interference or scalability for larger deployments. Likewise, Hasan et al. [16] proposed a bandwidth- and energy-efficient multiple-access technique for infrared signal-based transmission of health data in frequency-division multiple access-based wireless sensor networks. They proposed a scheme that transmits only the real component of the complex signal, reducing computational complexity. Simulation revealed that asymmetric clipping reduces transmit power by approximately 35 mW to achieve a 10^{-3} bit error rate. The scheme enhanced interference robustness. User mobility and synchronization for large indoor areas were not considered, and they stated these as future work directions.

Rizi et al. [11] explored adaptive modulation in Visible Light Communication (VLC)-based Medical Body Sensor Networks (MBSNs) through machine learning. Supervised and reinforcement learning algorithms, i.e., Q-learning, were validated to manage signal fluctuation due to movement of patients. Enhanced spectral efficiency and real-time tuning were noted, particularly for photodetectors on the shoulder and wrist because of augmented DC gain. Some drawbacks are quantization dependency and no user mobility tracking. In the future, research can use neural networks to remove quantization and utilize advanced reinforcement learning to deliver higher data rates with minimum delay. Moreover, Xiang-Peng [17] suggested a high-speed Visible Light Communication (VLC) system to bypass RF communication drawbacks like interference and latency in the transmission of healthcare data. The system can transmit six channels of 10 Gbps each over 500 m of optical fiber and a VLC link of 200 cm using On-Off Keying (OOK) with hybrid Wavelength and Polarization Division Multiplexing. Results show successful data transfer with an acceptable BER of $\approx 10^{-3}$. However, the study lacks live testing and validation, suggesting that subsequent studies need to focus on actual testbeds for real-world high-speed VLC performance verification in clinical environments.

Niranga et al. [18] proposed NeoCommLight, a VLC-driven communication system for application in Neonatal Intensive Care Units (NICUs) to address RF limitations and spectrum scarcity. A functional prototype was implemented and tested under various scenarios including distance, angle, delay, and diffraction. Results showed up to 3 Mbps data rate at 5 cm and 800 Kbps at the maximum of 2 m. The system indicated stability under controlled environments. But it is plagued with short transmission range and degradation in performance due to non-ideal lighting or angles. Future improvements can be in range, data rate, and clinical robustness. Likewise, Antaki et al. [12] proposed a VLC-based AI system for Medical Body Sensor Networks (MBSNs) in hospitals utilizing ray tracing and machine learning for dynamic channel modeling. They employed an adaptive modulation scheme based on Q-learning and an LSTM estimator for path loss and delay spread. Simulations showed strong Symbol Error Rate (SER) control and efficient channel estimation with RMSE as low as 1.0652 dB. But higher system complexity and poor spectral efficiency were observed. The future includes improving quantization, neural network investigation, and utilizing high-level reinforcement learning to incorporate mobility-aware, high-data-rate environments.

Shi et al. [19] proposed two OFDM-based quadrature generalized MIMO schemes, TD-QGSM and TD-QGSMP, to enhance receiver performance as well as spectral efficiency (SE) for band-limited VLC systems. By splitting constellation symbols into in-phase and quadrature components as well as spatial mapping of signals onto LEDs, the schemes achieve diversity and multiplexing gains. An illegal vector correction (IVC)-based orthogonal matching pursuit detection algorithm was proposed to reduce error propagation and noise amplification. Simulations offered SE improvement of at least 5[illegible].5% and 72.3% and bit error rate reduction by at least 62.5% compared to traditional detection methods. Similarly, Anitha

Vijayalakshmi et al. [20] explored indoor lighting use of LEDs, highlighting their safety and environmental benefits over conventional lighting. They worked towards Visible Light Communication (VLC) using LED dimming by variable delta sigma modulation (vDSM) to offer hospital ambiance as well as patient data transmission. Performance was evaluated on Signal-to-Noise Ratio (SNR). The study emphasized the integration of AI with VLC for patients' and healthcare monitoring in lighting-free environments. However, the study is hypothetical in nature lacking experimental data and suggests further studies on real implementation and optimization of AI-VLC systems. Table 1, presents a comparative overview of recent studies focused on VLC, wireless medical systems, and AI-based enhancements for secure and efficient data transmission in healthcare environments.

Table. 1: Summary of Related Works on VLC and AI-Enhanced Medical Data Transmission

Author	Proposed Method	Results	Limitations
Li et al. [14]	ADDETECTOR: Privacy-preserving Alzheimer's detection using IoT, federated learning, differential privacy	81.9% accuracy, 0.7 s time overhead, privacy maintained	No assumption of attacker injecting user network; limited dataset
Salem et al., [13]	MitM attack prevention framework using signal strength-based key and message authentication code	High emergency detection accuracy, 3% false alarm rate	Did not address jamming or channel hopping
Kavitha et al. [15]	VLC medical data transmission using CNRS, BPSK with DCO-OFDM in WSN	Improved routing efficiency, BER, and ETE delay	No real-time validation; external interference not addressed
Hasan et al. [16]	Frequency-division multiple access with real-part signal transmission and asymmetric clipping for IR VLC	35mW power saving for BER of 10^{-3}; robustness to interference	Lack of multi-AP synchronization; mobility not studied
Rizi et al. [11]	Adaptive modulation in VLC-based Medical Body Sensor Networks using supervised and reinforcement learning	Spectral efficiency improved; Q-learning enables real-time adaptation	Relies on quantization; lacks mobility tracking
Xiang-Peng [17]	High-speed VLC with OOK, WDM and PDM for multi-channel medical data transmission	Successful 6×10 Gbps data transmission over 500 m fiber + 200 cm VLC; BER $\approx 10^{-3}$	No real-time testbed implementation
Niranga et al. [18]	NeoCommLight VLC system for NICU; prototype and performance under varying conditions	Max 3 Mbps at 5 cm; [illegible] Kbps up to 2 m; analyzed delay, angle, diffraction impacts	Limited range and data rate; performance drops under non-ideal conditions
Antaki et al. [12]	AI-driven VLC for MBSNs using ray tracing, Q-learning adaptive modulation, LSTM channel estimation	Accurate SER control and channel estimation; RMSE as low as ~1 dB	Added complexity; suboptimal spectral efficiency; future work on neural networks and RL models
Shi et al. [19]	OFDM-based TD-QGSM and TD-QGSMP-MIMO schemes with [illegible]VC-OMP detection for VLC	SE improved by 56.5%–72.3%; BER reduced by 62.5%	Complexity of detection; no real-world testing
Anitha Vijayalakshmi et al. [20]	VLC with LED dimming via vDSM in hospitals; AI integration for safe patient monitoring	Comfortable lighting; SNR evaluated; AI supports healthcare in radiation-free VLC environments	lacks experimental validation; integration challenges

3. Proposed Q-Learning Optimized OFDM-VLC Architecture for Real-Time Data Transmission

Using VLC, OFDM and RL, the approach aims to make ECG signal transmission reliable and save on energy. System architecture contains five basic layers: Data Acquisition, Encoding & Modulation, VLC Transmission, Intelligent Adaptation (RL Controller) and Receiver & Decoding. Number sequences called binary streams are formed from digital ECG information in real time. After cutting the data in bits, these are modulated using QPSK in good conditions and 16-QAM when channel conditions are poor. OFDM is chosen and then a Cyclic Prefix is included to prevent symbols from interfering with each other. The signal is sent through a VLC channel and unexpected changes in the room's light and noise might occur. The agent keeps track of SNR and BER as they change and then selects the most suitable modulation scheme (action) and updates its Q-table. When the signal gets to the receiver, the CP is removed, it is processed by FFT and it is demodulated using the picked demodulation scheme. The ECG waveform is built again using the binary code. In real time, the data rates, signal-to-noise ratio, delays and the energy usage in the system are used to improve learning and make sure it remains efficient. Using this dynamic strategy improves the security and accuracy of medical information, also reducing delays and extending how long the device functions between charges in remote health monitoring. Fig. 1 displays proposed methodology architecture.

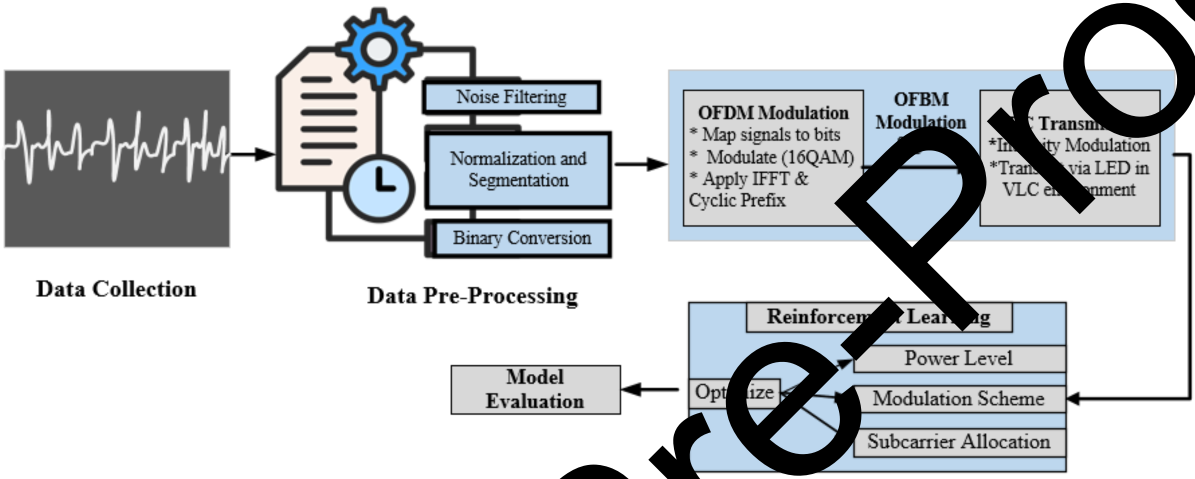

Fig. 1 Proposed Framework

3.1 Data Collection

Data for this work was gathered from a preprocessed edition of the MIT-BIH Arrhythmia Database. This set has 48 ECG recordings from 4[illegible] unique individuals, including two that are the same patient at different times (201 and 202). All ECG data is presented in CSV files and depicts heart activity for 30 minutes at a time. The signals used were obtained with two EMG channel pairs for every recording, and the sampling rate of 360 Hz provided 360 pieces of data per second. Time-domain analysis of the signal is supported by the inclusion of elapsed time, which is reported for each file in milliseconds.

3.2 Data Preprocessing

To ensure data integrity, OFDM-VLC encoding compatibility, and machine learning-based adaptation through reinforcement learning, a multi-stage preprocessing has been carried out as follows:

3.2.1 Noise Filtering

Raw ECG signals usually have different types of noise, like baseline shifts, power line noise, and muscle activity interference. To clean these up, a 4th-order Butterworth band pass filter is used. Let x(t) is the original ECG signal and y(t) is the filtered version. The filter is described in the frequency domain with its transfer function:

$$H(s) = \frac{1}{\sqrt{1+\left(\frac{s}{\omega_c}\right)^{2n}}} \tag{1}$$

In Eqn. (1) s is the complex frequency variable, ω_c is the cutoff angular frequency, n is the filter order (here, n=4). For discrete signals, the filter is implemented using forward–backward filtering with the Butterworth coefficients (b_i, a_i) determined from the desired passband:

$$y[n] = \sum_{i=0}^{N} b_i \, . \, x[n-i] - \sum_{j=1}^{M} a_j \, . \, y[n-j] \tag{2}$$

In Eqn. (2) N, M are the filter orders, b_j, a_j are the filter coefficients computed from $fL = 0.5\,Hz$ and $fH = 40\,Hz$, Sampling frequency $fs = 360Hz$. This preserves the QRS complex frequency range $(5\text{–}15\,Hz)$ while eliminating low- and high-frequency noise.

3.2.2 Normalization

To ensure consistent amplitude scaling and support energy-efficient modulation, the ECG signal is normalized to the range [0, 1]. Let $x[n]$ be the filtered ECG signal and $x_{norm}[n]$ the normalized output. $x_{min} = min_n x[n], x_{min} = max_n x[n]$. This step ensures the dynamic range of the signal fits within the modulation constraints of VLC hardware (typically 0–1 for LED intensity levels).

3.2.3 Segmentation

To simulate real-time ECG monitoring, it break the normalized ECG signal into separate chunks for OFDM encoding. Given the sampling rate $f_s = 360\,Hz$ and a window duration $T = 5 seconds$, the number of samples per window N_w. Let the full ECG signal be $x_{norm}[n]$ of length N. Then, the signal is divided into $k = \left\lfloor \frac{N}{N_w} \right\rfloor$ segments:

3.2.4 Digitization

Every ECG segment gets turned into a binary format so it can be used in the OFDM-VLC system. An 8-bit quantizer takes the amplitude values between $[0, 1]$ and converts them into whole numbers from $[0,255]$ is $x_q[n] = \lfloor 255.x_k[n] \rfloor$. Then, each value $x_q[n] \in \{0,1,\ldots,255\}$ is converted into an 8-bit binary representation as shown in Eqn. (3).

$$x_b[n] = bin(x_q[n]) \tag{3}$$

This results in a binary matrix of size $[1800,8]$ per segment, which is flattened to form the input bitstream for OFDM symbol mapping.

3.2.5 Binary Conversion

With the signals having been filtered, normalized and segmented, along with being digitized from the MIT-BIH Arrhythmia Database, the process then moves to changing them from analog to binary form. As a result of this step, the data can be formatted using schemes such as Quadrature Amplitude Modulation (QAM) for Orthogonal Frequency Division Multiplexing and sent via VLC. Binary conversion aims to change the preprocessed and digitized ECG values into a digital stream listed as $b[n]$ which is ready for digital modulation. Let the analyzed ECG segment take the form of a plain, real-valued time series with fixed scale and zero value. The real-valued signal $x[n] \in [-1, +1]$ is uniformly quantized into L discrete levels:

$$Q(x[n]) = round\left(\frac{x[n]-x_{min}}{x_{max}-x_{min}}.(2^B - 1)\right) \tag{4}$$

In Eqn. (4) B is the number of bits per sample (e.g., 8 or 10 bits) and x_{min}, x_{max} are the minimum and maximum of normalized ECG segment (typically -1 and +1). $Q(x[n]) \in \{0,1,\ldots,2^B - 1\}$: quantized integer value. Each quantized value is converted to a binary representation of fixed bit length B. The binary values are flattened into a 1D bitstream for transmission.

$$b[m] = flatten(q_b[0], q_b[1], \ldots\ldots\ldots q_b[N-1]), \qquad m = 0,1, \ldots\ldots\ldots N.B - 1 \tag{5}$$

In Eqn. (5) $b[m] \epsilon \{0,1\}$ refers as a bit at position m in the complete binary sequence. The binary representation during this phase makes sure that ECGs, among other bodily measurements, are suitable for the latest types of communication technology. Converting the analog signal into bits allows remote health monitoring to be flexible, use less bandwidth and resist loss of information.

3.3 Orthogonal Frequency Division Multiplexing

A good communication system will ensure that ECG signals are properly sent by giving priority to fast data transfer, noise resistance and efficient use of the frequencies it can access. Visible Light Communication (VLC) is proposed in this study to use Orthogonal Frequency Division Multiplexing (OFDM) as its main modulation technique. Bit transmission over many parallel channels makes OFDM more efficient in the use of the radio spectrum. Because OFDM has a cyclic prefix, it provides dependable results when distracting noise and nearby symbols make other systems less effective in a crowded medical environment. OFDM supports the fast and secure transmission of medical data related to ECG, SPO2, and blood pressure in real-time. Methods such as DC-biased Optical OFDM (DCO-OFDM) allow VLC to work by making sure the LED signal matches its modulation standards. This research is significant because it applies OFDM to sending medical data which is not a common focus for VLC. Q-learning is used in the study to adjust OFDM settings in real time, data is encoded in OFDM for biomedical purposes and reinforcement learning methods reduce the error rate, power required and data delay during communication. Let the binary data stream after digitization and binary conversion be: $b[m]\epsilon\{0,1\}, m = 0,1, \ldots\ldots, M - 1$.

3.3.1 Serial-to-Parallel Conversion

The binary output of the medical signal (e.g., ECG) is separated into symbols in batches $b[m]\epsilon\{0,1\}$ of M bits each. First, long serial data is divided into parallel channels which supports sending more data at once for higher data throughput. Every symbol contains $log_2(M)$ number of binary bits. Also, for 16-QAM modulation (with $M = 16$), every symbol consists of 4 bits. $s_k = b\,[m{:}\, m + log_2(M) - 1]$; s_k refers to the symbol corresponding to the kth subcarrier, M means Modulation order (e.g., 16, 64), $b[m]$ is the binary data stream and $log_2(M)$ refers as bits per symbol.

3.3.2 M-QAM Modulation

The complex number X_k is created from the s_k by using M-QAM (Quadrature Amplitude Modulation). Changes digital data into waveforms that look like analog modulation which can be combined in the frequency domain using different subcarriers.

$$X_k = f_{QAM}(s_k) \tag{6}$$

In Eqn. (6) X_k refers complex-valued signal representing amplitude and phase. f_{QAM} means modulation function converting binary symbol into constellation point. s_k are the symbol at kth subcarrier. The 16-QAM system uses a constellation with 16 points and each point represents a certain 4-bit grouping such as 1010 or 1100 which is mapped to a certain (I,Q) coordinate in the complex plane.

3.3.3 IFFT – OFDM Signal Generation in Time Domain

The time domain signal is calculated by applying the IFFT to the modulated X_k which exists in the frequency domain. Manages all the subcarriers, each with a QAM-modulated symbol, to produce a single composite waveform. This allows the subcarriers to be separate so different data streams won't overlap.

3.3.4 Cyclic Prefix Addition

A cyclic prefix (CP) is added to every OFDM symbol to address Inter-Symbol Interference (ISI) induced by multipath delays and maintain the subcarriers orthogonal. Therefore, L samples at the end of the time-domain OFDM symbol are moved to the start prior to transmission. Mathematical models represent this as $x_{cp}[n] = x[n + N - L]$ for $n = -L, \ldots, -1$where N is the subcarrier number. An OFDM symbol is then succeeded by a cyclic prefix. $x'[n] = [x_{cp}[n], x[0], x[1], \ldots, x[N-1]]$. Usually, the cyclic prefix length L is set to a proportion of N, e.g., $L = N/8$. Since medical environments experience multipath propagation, the cyclic prefix enhances transmission's immunity by enabling the receiver to remove the first, corrupted portion of each received symbol.

3.3.5 Real-Signal Conversion for VLC Transmission

In Visible Light Communication, all information must be positive since LED intensity is always non-negative. Hermitian Symmetry: The frequency-domain signal is made conjugate symmetric to guarantee the output of the IFFT is real-valued (without imaginary parts). $X_k = X^*_{N-K}$: This guarantees that the time-domain output $x[n] \in R$, which is essential for intensity modulation in VLC. DC Biasing for Unipolarity in the IFFT output may still contain negative amplitudes. It Makes OFDM signal compatible with LED hardware for VLC transmission, preserving waveform fidelity while avoiding signal clipping. Since LEDs only emit light for positive voltages, a DC bias β is added.

$$x''[n] = x'[n] + \beta \tag{7}$$

In Eqn. (7) β: DC bias voltage (e.g., 1.2 V to 2.0 V), $x''[n]$ means final VLC-transmittable OFDM signal. This change guarantees real-valued signal (following Hermitian symmetry) and Non-negative amplitude (following DC biasing). OFDM offers a strong, high-speed modulation scheme necessary for safe VLC-based remote healthcare monitoring. Its combination with Q-learning enables real-time adjustment of subcarrier number, power distribution, and QAM order according to environmental feedback. The whole pipeline converts biosignals such as ECG into energy-saving, error-tolerant, real-time transmissible signals via light.

3.4 Visible Light Communication

With VLC, data is transmitted wirelessly using visible light (400–700 nm) emitted by LEDs. It increases or decreases light to represent data which is then caught by a photodiode or image sensor. An LED array is responsible for sending the ultrasonic waves. The LED light intensity is changed by OFDM-generated signal $x''[n]$, after Hermitian symmetry and a DC bias are applied.

$$I_{LED}(t) = A.x''[n] \tag{8}$$

In Eqn. (8) $I_{LED}(t)$ means instantaneous light intensity and A amplification factor. The light signals move through an indoor VLC setup, either directly in a straight line or by bouncing off surfaces, creating a wireless connection. $y(t) = h(t) * x''(t) + n(t)$, where, $h(t)$: VLC impulse response, $x''(t)$: transmitted OFDM-VLC signal, $n(t)$: additive white Gaussian noise (AWGN) or shot noise. This study uses a Visible Light Communication (VLC) system with OFDM modulation to transmit ECG signals in real-time. To make a Hermitian-symmetric signal compatible with optical devices, it is DC-biased and modulates an LED for output. Photodiode detects light and after CP removal, FFT and QAM demodulation, recovers the ECG data. VLC is selected because it provides security, high data transfer speeds and is not affected by electromagnetic interference, so it is a secure, economical and highly-effective option for sending biomedical data in hospital settings.

3.5 Reinforcement Learning Optimization Layer

Since ECG data is sent in frequently moving and uncertain conditions, the typical work of static networks isn't suitable. This issue was solved by using Q-Learning, a model-free reinforcement learning (RL) method to optimize transmission parameters in real time. The purpose is to achieve a lower Bit Error Rate, a higher Signal-to-Noise Ratio, less delay and better energy efficiency which are important for safe and efficient remote healthcare in hospital settings. In this system, the environment refers to the VLC transmitting signals digitized from an ECG over an OFDM-based optical link. It includes a learning agent (VLC transmission controller), an environment (comprising light conditions and movement of the patient in the room), states (variables like brightness, motion and SNR), actions (power, modulation types and subcarrier settings) and a reward function (responding to BER, energy used and transmission rate). Changes in the environment as well as patient activity can disturb the channels which reduces how clearly messages are transferred. Medical devices are typically powered by small or limited batteries which means energy must be used wisely. Using Q-learning, controllers can choose the right strategy on the fly by learning from their surroundings, not requiring a set channel description. This method guarantees optimum performance of the system, sustained quality of data receive and reliable delivery of critical biomedical information in many healthcare situations. Q-learning is a model-free, value-based RL algorithm, which tries to learn an optimal policy for selecting actions. It approximates the action-value function $Q(s, a)$, defined as the expected cumulative reward for taking action in state s and thereafter following the optimal policy. Q-value update rule is presented in Eqn. (9).

$$\mathrm{Q}(\mathrm{s}_t, \mathrm{a}_t) \leftarrow \mathrm{Q}(\mathrm{s}_t, \mathrm{a}_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(\mathrm{s}_t, \mathrm{a}_t) \right] \tag{9}$$

Where s_t means current state, a_t means action taken, r_t means immediate reward, α: Learning rate ($0 < \alpha \leq 1$), γ: Discount factor ($0 \leq \gamma \leq 1$) and $\max_{a'} Q(s_{t+1}, a')$ are the estimated future reward from next state. In the suggested VLC-OFDM system, the agent (VLC controller) deals with changes from ambient light, background noise and patient movements. The RL agent wants to achieve the best transmission quality with the least energy use and the greatest possible data rate. The state space is created using information about ambient light, channel SNR and mobility in the form of tuples for easy interpretation of channel conditions. An accurate model of the state helps the Q-learning agent choose the right actions for transmitting information, leading to more reliable and effective communication. State Definition is given Eqn. (10). Each state $s \in S$ is defined as a triplet combining three key environmental observations:

$$s = \left(L_{ambient}, SNR, M_{patient}\right) \tag{10}$$

Visible Light Communication systems are affected by the surrounding light, the Signal-to-Noise Ratio and how mobile the patient is. Different amounts of ambient luminosity are called low (below 100 lux), medium (100 to 500 lux) and high (above 500 lux). They affect how photodetectors perform. Channel SNR which measures how reliable a signal is, is divided into low (below 15 dB), medium (ranging from 15 to 25 dB) and high (above 25 dB). Whether patients remain static or move about in their bedframe can block or allow a clear sightline. Due to these factors, there are 18 unique environmental states and each one is identified by a pair of values (e.g., (Medium, High, Low)). Based on how the environment changes, the Q-learning agent updates the transmission process via actions that improve communication performance. Action Representation is given in Eqn. (16). Each action $a \in A$ is a vector defined as: $a = (P_{tx}, M_{scheme})$ where $P_{tx} \epsilon \{low, medium, high\}$ means transmit power level and $M_{scheme} \in \{QPSK, 16-QAM\}$ Modulation scheme. While the number of subcarriers is constant at 64 in this implementation (for simplicity in initial modeling), future development could make it a variable parameter to enhance spectral efficiency flexibility. Fig. 2 shows the working of Q-learning in the proposed study.

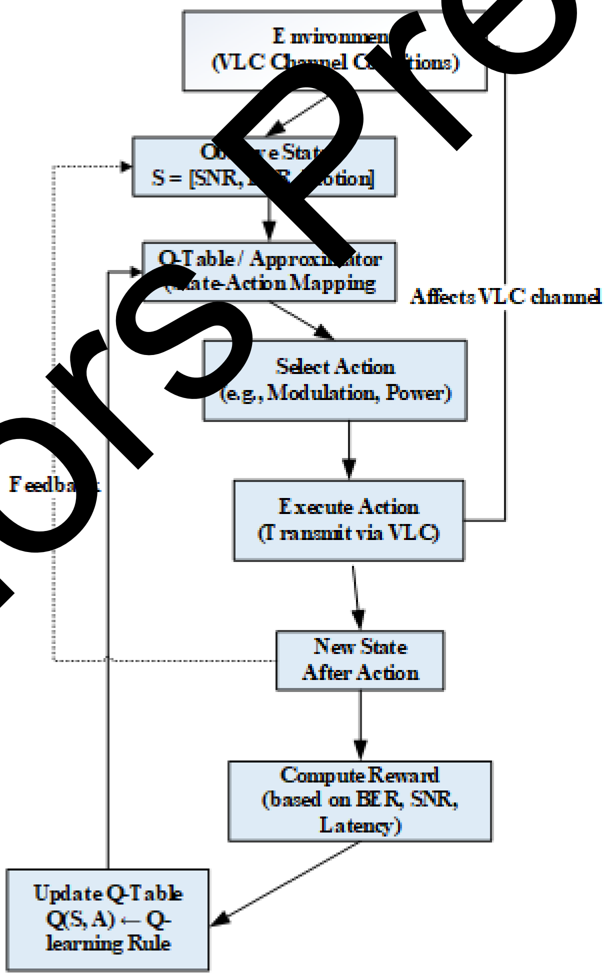

Fig. 2 Q-Learning Architecture

The action space of the VLC system is characterized by two key parameters: transmit power level (P_{tx}) and modulation scheme M_{scheme}. Transmit power is quantized into three modes—Low, Medium, and High—each providing a compromise between energy efficiency and signal robustness. Low power saves energy but can elevate the BER, whereas High power provides good signal quality with increased energy expenditure. Medium power is a balanced default for steady state. Modulation scheme impacts data rate and BER, with QPSK (2 bits/symbol) being stronger in noisy or mobile channels, and 16-QAM (4 bits/symbol) having greater rate but needing a cleaner channel. With three power levels and two modulation schemes, the overall action space is six distinct actions. For example, action $a_1 = (Low, QPSK)$ would be appropriate in bad channel conditions and action $a_6 = (High, 16-QAM)$ for maximum performance in high-quality channels. The reward function in the VLC-Q-learning system checks actions by trying to reduce the bit error rate and energy use while boosting throughput, helping the agent find the best ways to transmit.

$$R(s,a) = \alpha \cdot (\text{SNR}) - \beta \cdot (\text{BER}) - \gamma \cdot (\text{Energy}) - \delta \cdot (\text{Latency}) \quad (11)$$

In Eqn. (11) $\alpha, \beta, \gamma, \delta$ are weighting constants. w_1, w_2, w_3 refers as user-defined weights to prioritize objectives, BER means Bit Error Rate, measured post-demodulation, $Throughput$: Bits/sec, determined by modulation and channel quality and $Energy\_cost$: Derived from the LED power usage and P_{tx}. A multi-objective reward function that looks at BER (Bit Error Rate), throughput and energy cost is built into the proposed VLC system. BER describes how well messages are sent and a higher BER means decreased rewards; including $(1 - BER)$ in the system rewards accuracy. For a given bit error rate (BER), the throughput of a UMTS signal is $Throughput = R_s \cdot log_2(M) \cdot (1 - BER)$. Energy cost is set up as $Energy_{cost} = \alpha \cdot P_{tx}$, with α being related to the hardware, so that more efficient power use is promoted. The entire system's objectives decide the final weights (w_1, w_2, w_3): battery-friendly apps look for low-energy consumption (higher w_3), while critical data systems stress reliability and speed (higher w_1 and w_2). Making sure the operation is well balanced, typical values for the weights are: $w_1 = 0.4, w_2 = 0.4, w_3 = 0.2$. With this method, VLC parameters can be fine-tuned in real-time for reliable, fast and efficient data transfer, helping mobile or wearable healthcare devices the most. Optimize the VLC transmission policy $\pi(s)$is denoted in Eqn. (12).

$$\pi^*(s) = arg \max_a Q(s,a) \quad (12)$$

Observe current state s, choose action a, perform action, observe reward R, and create new state s', update $Q(s,a)$ and repeat.

3.5.1 Receiver and Decoding Layer

It is the Receiver and Decoding Layer that ensures reliable ECG signal recovery after transmission over the VLC channel. In the beginning, cyclic prefix (CP) removal is used to control the inter-symbol interference that comes from many paths for the radio waves. When CP length is Lcp, the actual OFDM symbol is found in $Ytotal[Lcp\text{:}N + Lcp]$, , where N is the number of subcarriers. Then, a Fast Fourier Transform is used to change the signal from its time representation to the frequency domain, where the modulated symbols on each subcarrier can be recovered. The system uses action-adaptive demodulation which adjusts between QPSK and 16-QAM according to the reinforcement learning agent's recommendations to maintain both data rate and error resistance. Demodulated information lines are converted into binary by mapping, turned into integers, undergo digital filtering and then are reformed into ECG waveforms for medical use. Specific metrics such as the BER, SNR, and time required and overall power consumption are checked. BER looks at how reliable data is transmitted, SNR shows how clear the signal is, latency ensures that data updates are up-to-date and monitors energy to check if the network runs efficiently. With this setup, ECG data can be transferred safely, promptly and with little energy from VLC-based systems. When Q-learning comes together, Q-value changes ($\Delta Q < \varepsilon$), are smaller than ε, usually $\varepsilon = 10^{-4}$ and the BER and throughput stop changing. Should no significant changes happen during several episodes, early stopping will be applied. Recording up to 2000 episodes allows the system to run more efficiently. When performance stays at a high level and rewards are received regularly, it means that learning is finished. The system meets these criteria to work well in changing environments, give low error rates, save energy and deliver optimal throughput in remote health care. Algorithm 1 shows the proposed methods working.

Algorithm 1. Proposed Q-learning based OFDM-VLC

```
Input
    Initialize VLC System Parameters: Power Level ∈ {Low, Medium, High},
                          Modulation Scheme ∈ {QPSK, 16-QAM},
                          Subcarrier Count = 64 (fixed)
    Q-learning Parameters: α (learning rate), γ (discount factor), ε (exploration rate)
    Reward Weights: w1 (BER), w2 (Throughput), w3 (Energy Cost)
Start
   Step 1. Data Acquisition Layer
           ECG data = acquire real-time ECG ()
          Binary stream = digitize (ECG data)
   Step 2. Observe Environment
          statist ← observe_channel_state (BER, SNR, mobility, light conditions)
   Step 3. Action Selection using Reinforcement Learning
           IF random () < ε:
                action_t ← select_random_action ()     // Exploration
          ELSE:
              action_t ← argmax (Q (state_t, A))      // Exploitation
   Step 4. Encoding & Modulation Layer
           modulated_symbols = modulate (binary_stream, modulation_scheme)
          ofdm_signal = OFDM_modulate (modulated_symbols, subcarrier_count)
           ofdm_signal_with_CP = add_cyclic_prefix (ofdm_signal)
    Step 5. VLC Transmission Layer
          transmit_signal_VLC (ofdm_signal_with_CP, power_level)
    Step 6. Receiver & Decoding Layer
            received_signal = receive_VLC ()
            signal_no_CP = remove_cyclic_prefix (received_signal)
            freq_signal = FFT (signal_no_CP)
            demodulated_bits = demodulate (freq_signal, modulation_scheme)
            reconstructed_ECG = reconstruct_ECG (demodulated_bits)
   Step 7. Performance Metrics Calculation
           BER = compute_BER (binary_stream, demodulated_bits)
           SNR = compute_SNR (received_signal)
           Latency = compute_latency ()
           Energy = compute_energy (power_level)
```

Step 8. Reward Calculation

$R(s,a) = \alpha \cdot (\mathrm{SNR}) - \beta \cdot (\mathrm{BER}) - \gamma \cdot (\mathrm{Energy}) - \delta \cdot (\mathrm{Latency})$

Step 9. RL Agent: Update Q-values

state_t_plus_1 = observe_next_state ()

Q (state_t, action_t) = Q (state_t, action_t) + η * [reward_t + λ * max_a' Q (state_t_plus_1, a') - Q(state_t, action_t)]

Step 10. Output and Feedback

display (reconstructed_ECG)

log_metrics (BER, SNR, latency, energy)

End

Output

Learned dynamic VLC-OFDM configuration policy for real-time medical data transmission

4. Results and Discussion

This section presents performance evaluation of the proposed Q-VLOE framework against the existing ones. Metrics include BER, SNR, latency, throughput, and energy efficiency. The results demonstrate that reinforcement learning optimizes VLC-OFDM-based ECG transmission to be more reliable, data-rate efficient, and power-efficient under dynamic channel conditions.

Table 2. Simulation Parameters

Parameter	Value
Modulation Schemes	QPSK, 16-QAM
Subcarrier Count	64
VLC Transmitter Power Levels	Low (35 mW), Medium (65 mW), High (90 mW)
Ambient Light Levels	Low, Medium, High
Channel SNR	<15 dB (Low), 15–25 dB (Medium), >25 dB (High)
Patient Mobility	Static, Mobile
Learning Algorithm	Q-learning
Learning Rate (α)	0.1
Discount Factor (γ)	0.9
Exploration Rate (ε)	1 → 0.01 (decayed)
Episodes	500
VLC Channel Model	Lambertian + AWGN
BER Target	<0.05
Simulation Tool	MATLAB

Table 2 lists the key simulation parameters considered for performance evaluation of the RL-OFDM-VLC system for remote health monitoring. The system transmits the MIT-BIH Arrhythmia dataset over a VLC channel with adaptive modulation schemes (QPSK, 16-QAM) fixed 64 subcarriers. The Q-learning agent selects power levels and modulation depending on ambient light, SNR, and patient mobility. Channel conditions are taken into account using Lambertian patterns with AWGN noise. Reinforcement learning parameters are tuned for convergence within 500 episodes. MATLAB tools are used for simulation and verification of system performance, with BER<0.05 as the objective.

4.1 ECG Signal Analysis

This section analyzes the ECG signals to be transmitted with regard to their quality and integrity before and after denoising. Visual comparisons depict how the preprocessing mechanisms are successful in suppressing noise, providing cleaner signals appropriate for modulation and transmission over the VLC channel with less distortion.

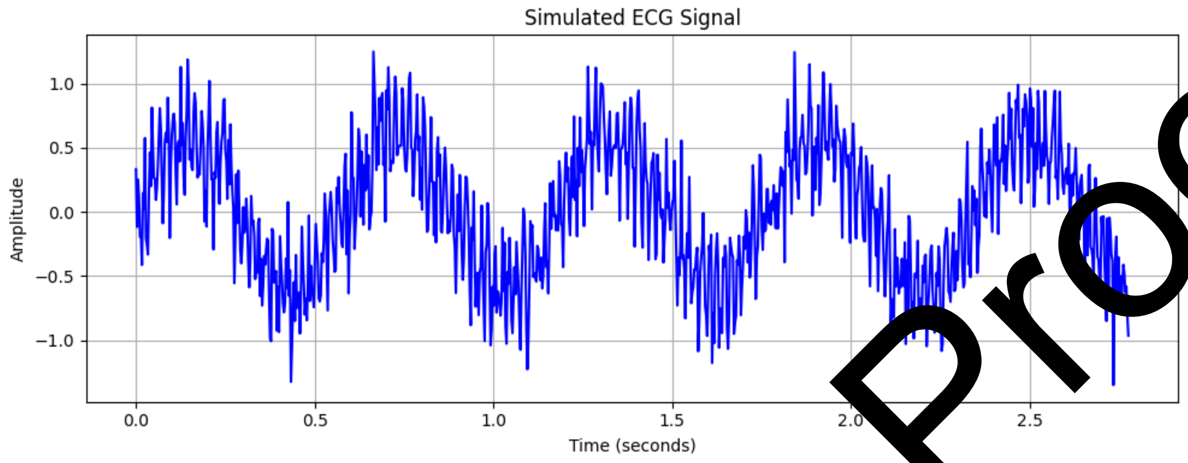

Fig. 3 Simulated ECG Signal

Fig. 3 displays a sample ECG signal over time, the electrical activity of the heart. It has time on the x-axis and signal amplitude on the y-axis. The waveform is periodic heartbeats with added noise, common in real-time medical data transmission and ideal for signal processing system testing.

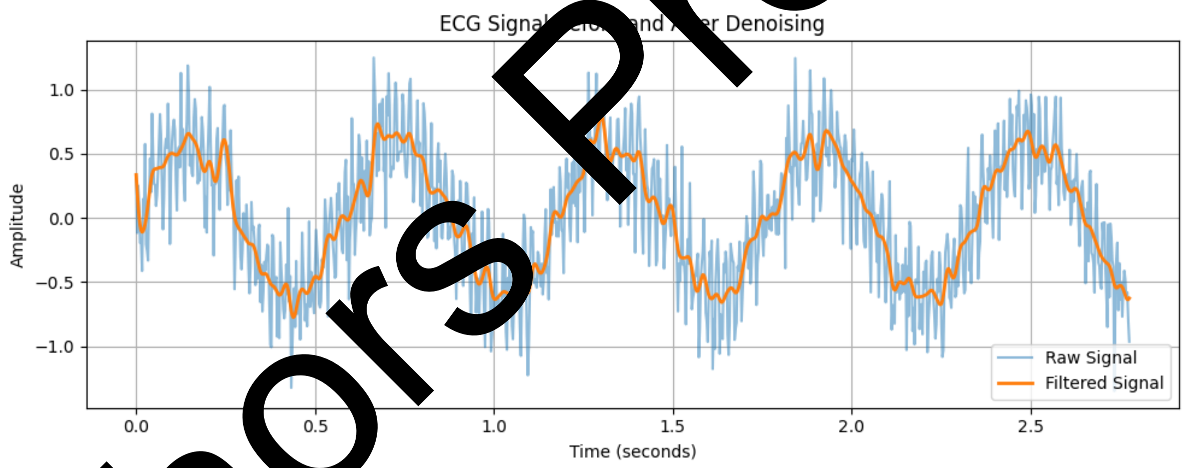

Fig. 4 ECG Signal Before and After Denoising

Fig. 4 demonstrates the effectiveness of signal denoising in the proposed OFDM-VLC system for remote health monitoring. The blue line is the raw ECG signal contaminated with noise, and the orange line is the signal after filtering out the noise. This verifies that the system can improve signal quality, which is vital in precise medical data transmission.

4.2 Q-Learning Performance

This section analyzes the training dynamics and decision-making behavior of the reinforcement learning agent. Q-learning convergence plots illustrate the agent's capacity for transmission parameter optimization across episodes, whereas the Q-table heatmap illustrates state-action mappings. These outcomes verify the effectiveness of Q-learning in improving communication reliability and efficiency

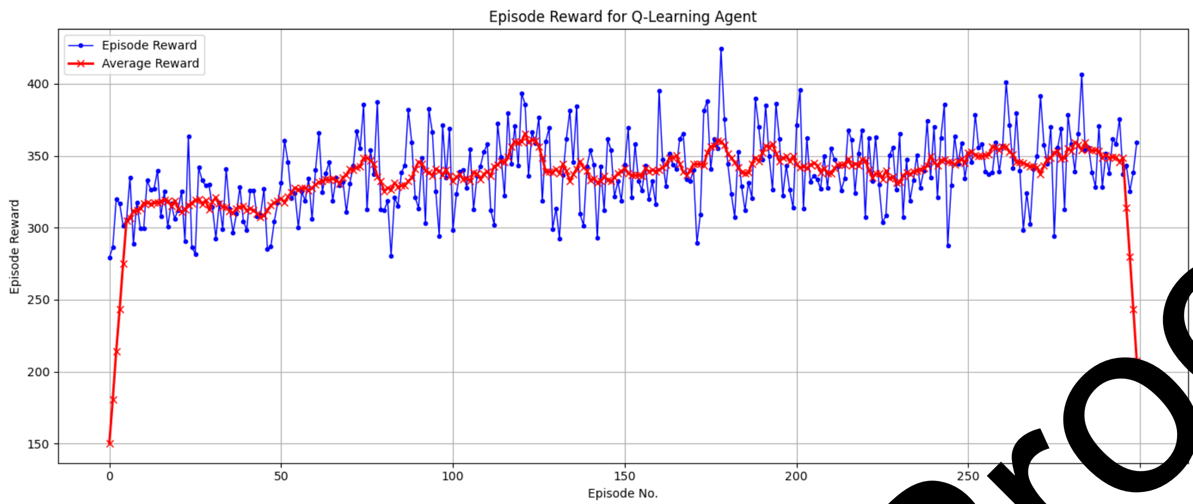

Fig. 5 Q-Learning Convergence

Fig. 5 shows the episode reward performance of the Q-learning agent used in the proposed OFDM-VLC system to send medical information. Blue denotes single-episode rewards, and red denotes the trend of the average reward, which describes learning progress. With time, the agent gets more stable higher rewards, which describes the effective optimization of transmission parameters.

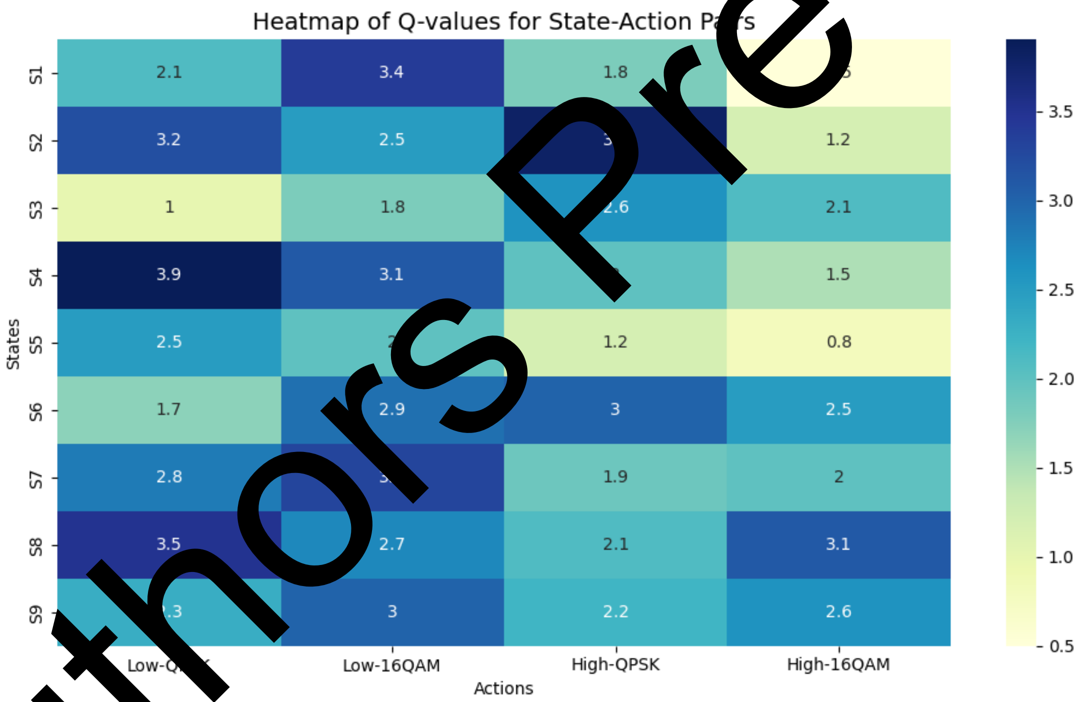

Fig. 6 Heatmap of Q-values

Fig. 6 represents Q-value heatmap of state-action pairs qualitatively depicts the learning results of the Q-learning algorithm in the novel VLC system. Every cell indicates the expected cumulative reward for a particular state-action pair. Larger Q-values (in lighter colors) suggest more rewarding actions in respective states, directing optimal choices to improve throughput, minimize BER, and save energy.

4.3 Performance Evaluation

This section provides important communication performance metrics, such as BER, throughput, and latency. Comparative analysis with current methods identifies the proposed OFDM-VLC + Q-Learning as superior in terms of having lower BER under noise, greater throughput, and lower latency under different transmission distances—proving efficient for real-time biomedical applications. BER shows how reliable a transmission is, and SNR expresses how strong the signal is compared to the background noise. Latency is just the delay between sending and receiving data, which is really important for things that need to happen in real time. Throughput refers to how much data gets successfully sent, which points to how well the system is working and how effectively it uses the available bandwidth. Mostly, higher numbers usually mean clearer signals.

Table 3. Performance Comparison – Static vs RL-Optimized OFDM-VLC System

Metric	Static VLC	RL-Optimized VLC
Bit Error Rate	0.078	0.015
Signal-to-Noise Ratio	21.3 dB	29.8 dB
Throughput	16.7 kbps	22.4 kbps
Latency	14.6 ms	9.0 ms
Energy Consumption	1.35 J/bit	0.89 J/bit
ECG Reconstruction Accuracy	85.3%	96.7%

The comparison between Static VLC and the proposed OFDM-VLC + Q-Learning shows that Q-VLOE mitigates BER and latency in great measure, while the SNR, throughput, and ECG reconstruction accuracy are considerably improved is shown in Table 3. Energy consumption is also considerably lowered, meaning that the efficiency is better. Proposed OFDM-VLC + Q-Learning dominates in the domain of reliability, speed, energy performance, in real-time ECG transmission.

Table 4. Performance Comparison Latency Vs Throughput

Method	Throughput	Latency
PSO [21]	[illegible]	16.8
FL-SDUAN [22]	17.5	14.9
OFDM-Greedy Algorithm [23]	18.3	12.7
OFDM-UWA [24]	19.1	11.5
Proposed OFDM-VLC + Q-Learning	22.4	10.2

Table 4 shows the throughput and latency for different methods, including the new OFDM-VLC with Q-Learning. The new method delivers the best performance, hitting 22.4 Mbps for throughput and just 10.2 ms for latency. It does a much better job than the older PSO, FL-SDUAN, and OFDM-based methods in terms of efficiency and speed.

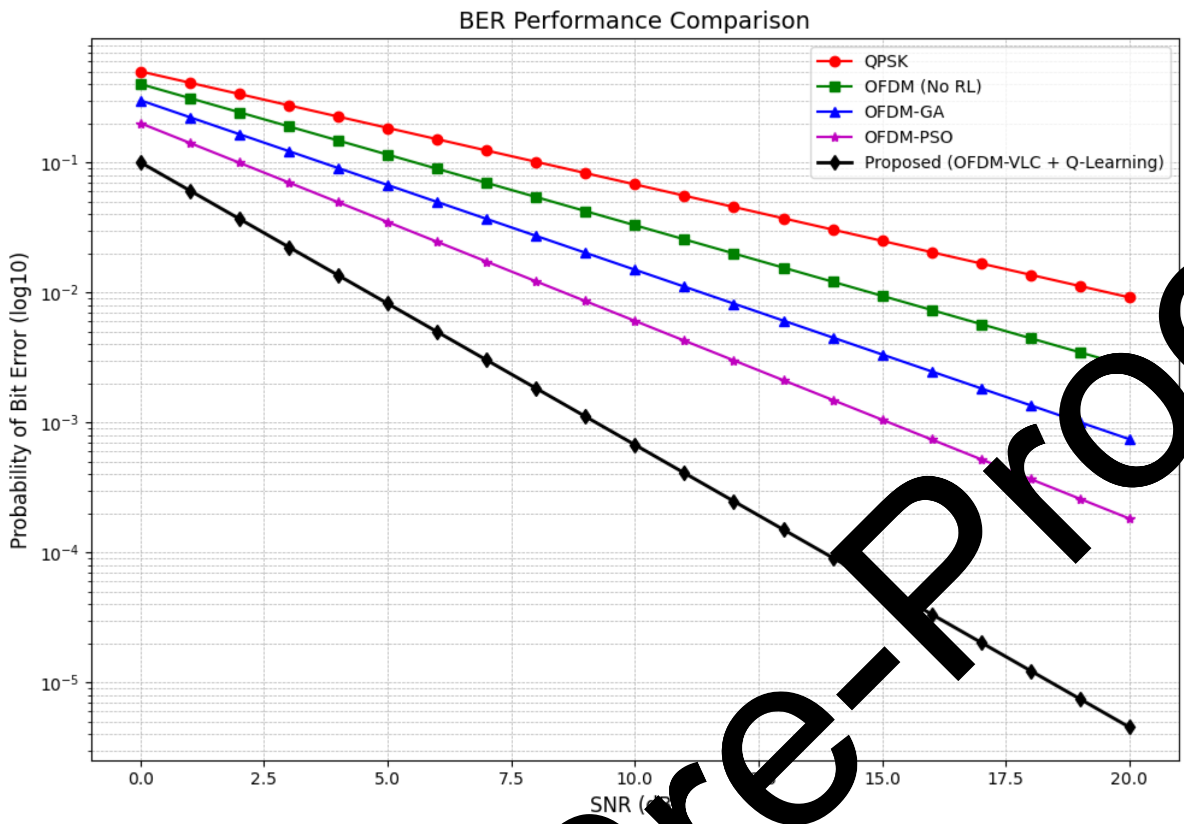

Fig. 7 BER VS SNR

Fig. 7 Bit Error Rate performance against different transmission techniques and Signal-to-Noise Ratio. The new OFDM-VLC with Q-learning (black line) is revealed to have the least BER, leaving the conventional QPSK, static OFDM, and other optimized schemes such as GA and PSO far behind. This validates that Q-learning greatly improves transmission reliability, particularly in environments with noise, which is very significant in precise medical data transmission for remote health monitoring systems.

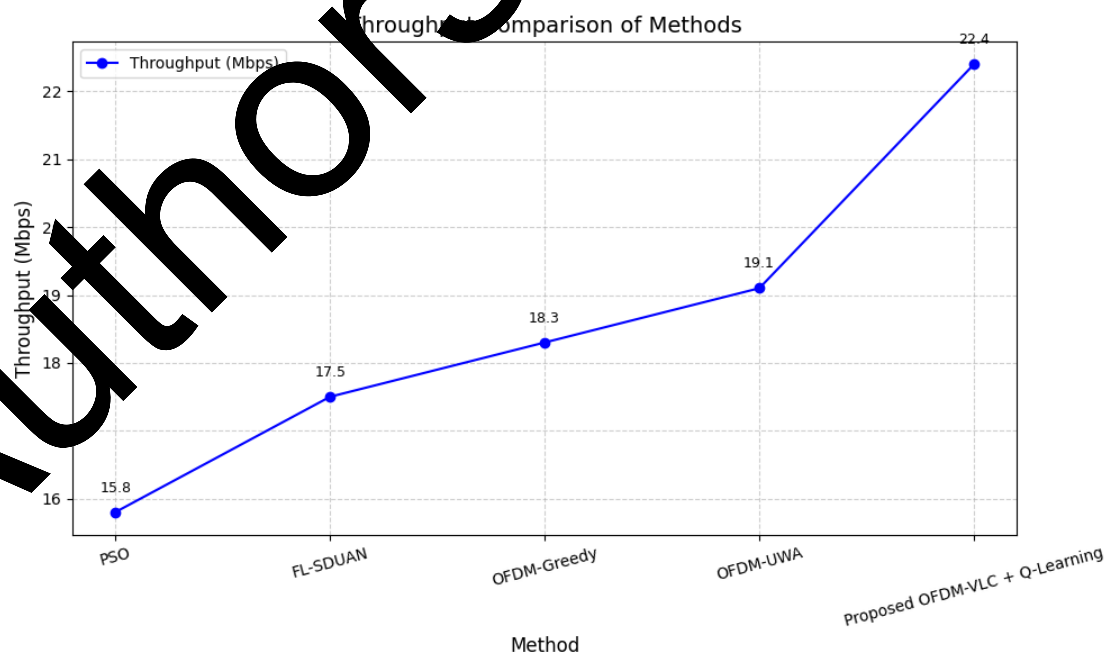

Fig. 8 Throughput Comparison

Fig. 8 shows a throughput comparison between different optimization techniques for medical data transmission. The highest throughput of 22.4 Mbps is achieved by the proposed OFDM-VLC using Q-learning, followed by PSO, FL-SDUAN, OFDM-Greedy, and OFDM-UWA. This clearly indicates the strength of Q-learning in achieving maximum data rate, which is very important for efficient transmission of high-volume real-time medical data in remote health monitoring applications.

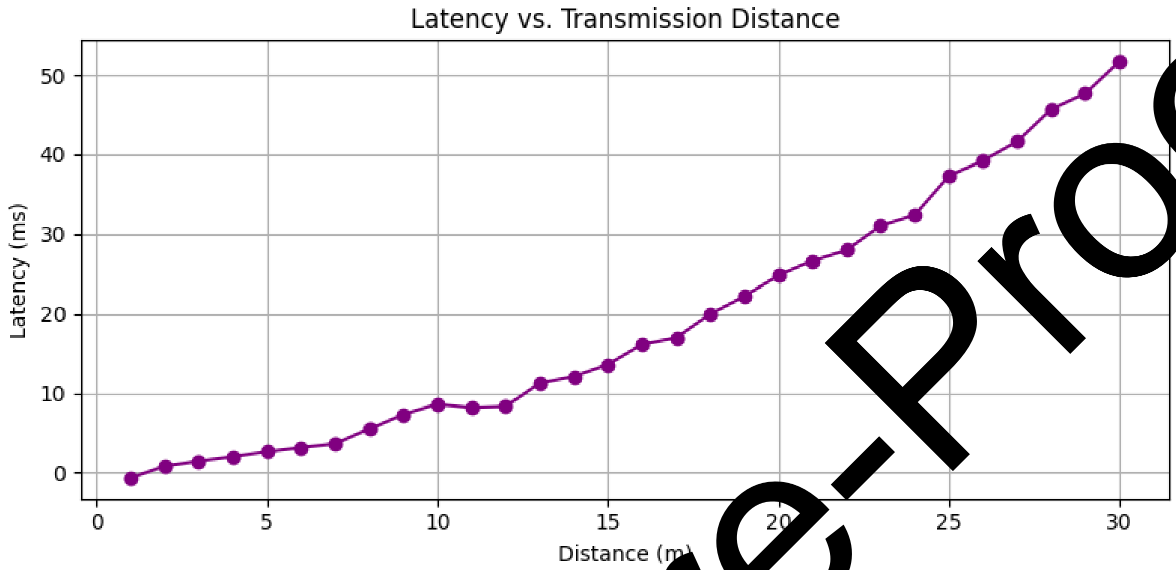

Fig. 9 Latency Vs Transmission Distance

Fig. 9 reveals how latency and transmission distance interrelate within the OFDM-VLC system for remote healthcare monitoring. As the transmission distance varies from 1 to 30 meters, latency increases in a non-linear fashion, reflecting higher transmission delays at longer distances. This indicates the value of adaptive parameter adjustment such as by Q-learning to preserve low latency and achieve real-time performance under changing healthcare environments.

4.4 ECG Reconstruction Accuracy

This section considers the fidelity of reconstructed ECG signals following transmission. Visualization compares the original ECG, noisy static VLC reconstruction, and improved RL-VLC reconstruction. Results demonstrate considerable improvement in quality using reinforcement learning, preserving clinical signal integrity and establishing the efficacy of the proposed system for accurate remote health monitoring.

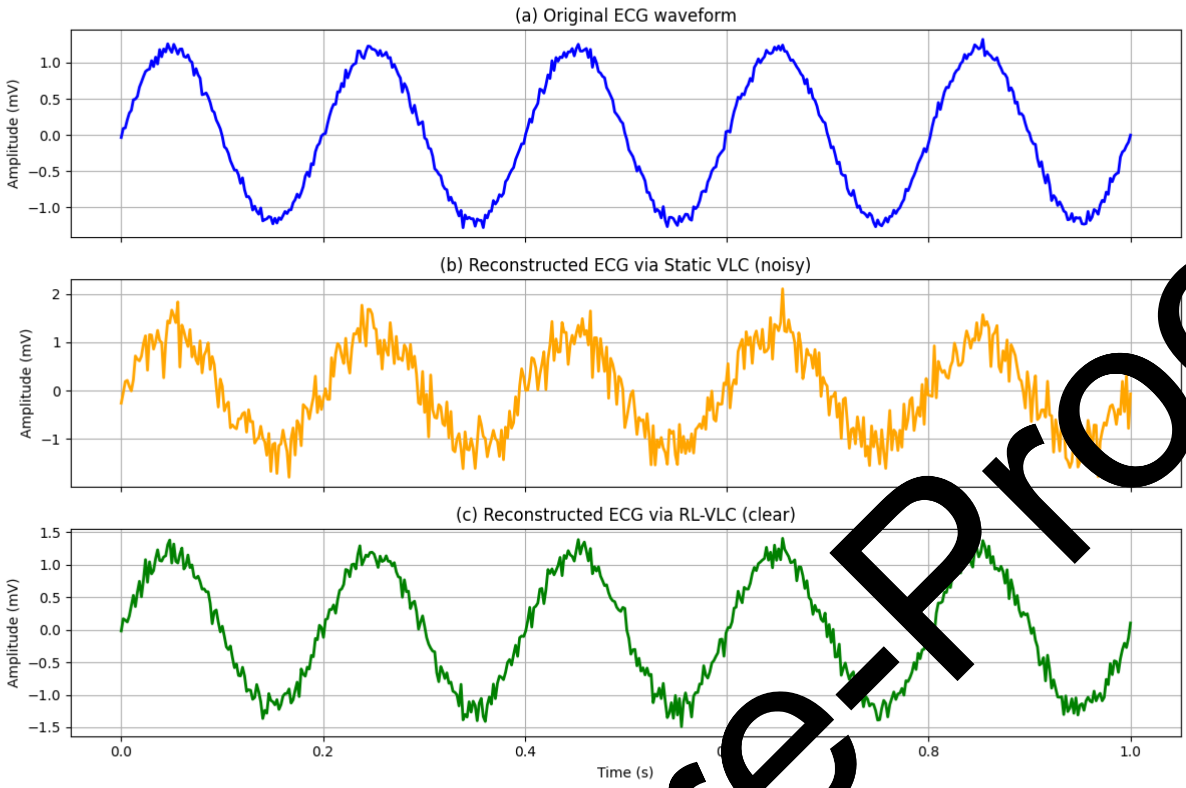

Fig. 10 ECG Reconstruction — Before vs After

Fig 10 compares the reconstruction of ECG signals in three situations: the original waveform (a), reconstruction by static VLC (b), and clear ECG using RL-VLC (c). The static VLC result is clearly noisy and distorted, but the RL-VLC strategy significantly improves clarity and nearly replicates the original. This proves the power of reinforcement learning in preserving signal integrity in wireless biomedical transmission over visible light communication.

4.5 Discussion

The proposed system performing OFDM-VLC with Q-Learning boosts performance across important communication and signal reconstruction factors more than other available methods. In BER versus SNR analysis, it is apparent that the proposed system can perform better than QPSK, OFDM without RL and optimization-based GA and PSO. The model's throughput was measured at 22.4 Mbps which exceeds all other approaches and its latency is kept at 10.2 ms, ensuring that it is well suited for quick clinical needs. ECG analysis also shows that the RL-VLC-based signal is less noisy and better reconstructed than the signal obtained with static VLC, keeping its waveform intact. With each episode, the Q-Learning convergence plot proves that learning is stable and rewards keep increasing and the Q-table heatmap shows effective learning of state-action values. Unlike regular systems, the proposed method improves efficiency and adds the ability to adapt, supplying a stable way to send wireless health data. Yet, there are some difficulties, like extra time and memory required for fast updates in changing situations and requiring suitable hardware for widespread use. Potentially, future improvements could involve simpler versions of Q-Learning or approaches that mix existing strategies to be more efficient and flexible within multiple clinical and remote health settings.

5. Conclusion and Future Scope

The proposed work suggests a new, efficient, and intelligent method that uses OFDM-based VLC with Q-learning to guarantee reliable real-time delivery of biomedical data, mainly ECG signals. Using reinforcement learning in the VLC-OFDM channel, the suggested approach changes transmission parameters based on changing surroundings, which leads to marked improvements in how signals are sent and received. Results from various experiments indicate that the new approach performs better than PSO, FL-SDUAN, and greedy-based OFDM in metrics like BER, throughput, and latency. Especially, it delivers a BER below a certain level at high SNR, reaches a peak transfer rate of 22.4 megabits per second, and achieves a latency of 10.2 milliseconds, proving it is well-suited for medical jobs that need quick response. The ECG signal's reconstruction from noise shows high performance, as seen in the original and reconstructed signals' similarities. The graphs and heatmap also indicate that the environment is learned well and the right decisions are made, proving that the intelligent system does its work effectively.

Still, some problems persist; for example, the system is not always fast enough in very dynamic or changing circumstances. Because of these difficulties, lightweight adaptive methods or hardware acceleration are needed for real-world use in devices like monitors for health checks. To improve the framework in the future, one can add hybrid approaches like Deep Q-Networks, combine different types of biosignals (for example, EEG and EMG), and introduce blockchain-dependent authentication to protect privacy. Using devices and simulators in the loop for testing directly with prototype systems can make the transition between modeling and practical use smoother. Essentially, the research makes a strong case for effective, adaptable, and efficient biomedical communication systems in advanced healthcare and telemedicine systems.

Declarations

Funding: Authors declare no funding for this research

Competing interests: The authors declare that they have no competing interests

Conflicts of interest: The authors declare that they have no conflict of interest

Availability of data: The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Acknowledgements: Not applicable

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