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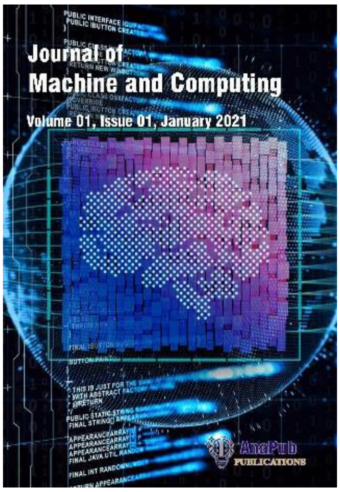

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Q-Learning Optimized EACDO-OFDM and IoT Framework for VLC-Enabled Smart Indoor Infrastructure

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Abstract

The proposed Q-learning optimized Internet of Things (IoT) integrated VLC system is highly suitable for indoor environments where electromagnetic interference (EMI), device density and real-time data transmission are critical challenges. Visible Light Communication (VLC) serves as an effective alternative to traditional RF communication by utilizing existing LED lighting infrastructure for dual-purpose illumination and data transmission. In such indoor settings the system enables real-time monitoring and secure transmission of vital information such as environmental data to an IoT-based cloud platform. The use of VLC in the visible light spectrum eliminates EMI making it ideal for environments where Radio Frequency (RF) communication is either restricted or unreliable. To adapt to dynamic indoor conditions such as human movement or changing light intensities the system employs Q-learning to continuously optimize transmission parameters like modulation index and power levels. This reinforcement learning approach ensures enhanced link reliability, reduced Bit Error Rate (BER) and stable communication under fluctuating indoor conditions. Additionally the incorporation of Enhanced Asymmetrically Clipped Duty-Cycled Optical OFDM (EACDO-OFDM) improves spectral efficiency and power utilization thus making the solution energy-efficient and scalable for large-scale indoor IoT deployments. By integrating adaptive machine learning techniques with VLC and IoT the system delivers robust, intelligent and energy-conscious communication, well-suited for smart building automation, indoor sensing and real-time monitoring applications.

Keywords: IoT, VLC, Q-Learning, Indoors, EACDO-OFDM, Li-Fi

1. Introduction

VLC is a cutting-edge wireless communication technology that utilizes LED-based light sources to transmit data by rapidly modulating the intensity of light [1]. The convergence of VLC and the IoT is revolutionizing indoor smart environments by enabling secure, efficient and interference-free data transmission [2]. These advantages make VLC particularly suitable for sensitive indoor spaces such as research labs, industrial control rooms or areas with RF-restricted equipment, where traditional RF-based wireless signals may cause disruptions. By integrating VLC with IoT the real-time monitoring systems can be implemented to ensure continuous tracking of critical parameters such as environmental conditions, equipment status or human activity [3]. Data collected from various sensors is transmitted through VLC enabled LEDs to an IoT-based cloud platform thus allowing stakeholders to access, analyse and respond to changes in real time as shown in figure 1. This enhances situational awareness, supports automation and reduces the need for constant manual supervision. Moreover the VLC technology helps to reduce network congestion by offloading traffic from traditional RF-based systems and therefore ensuring faster and more reliable communication. This is particularly beneficial in environments where uninterrupted data flow is crucial for operational safety, process control or timely decision-making [4].

Beyond conventional monitoring applications the Light Fidelity (Li-Fi) based Indoor Positioning Systems (IPS) play a transformative role in enhancing smart indoor automation. Leveraging high-speed and light-based communication the systems enable precise and real-time indoor navigation for individuals within complex infrastructures such as airports, shopping malls, industrial facilities, corporate campuses and educational institutions. Users including employees, visitors or maintenance personnel can seamlessly locate specific rooms, service areas or equipment without confusion or delay thus improving user experience and operational efficiency. In addition to navigation the Li-Fi IPS can be integrated with automated alert and notification systems to facilitate instant communication between different stakeholders. For instance in industrial or commercial settings the alerts can be triggered for critical system failures, security breaches or equipment malfunctions thus ensuring that support teams are informed promptly. This enhances resource coordination, safety protocols and response time's therefore allowing organizations to prioritize urgent tasks, reduce downtime and maintain smooth operational flow. Overall the Li-Fi IPS contributes significantly to the development of intelligent, responsive and connected indoor environments.

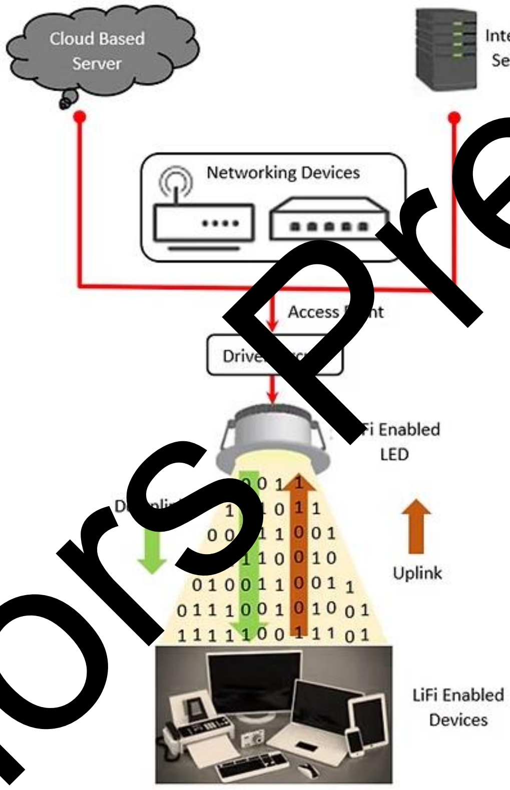


Fig 1. Working of Li-Fi

The IoT integrated VLC system can be further enhanced by incorporating Artificial Intelligence (AI) and Machine Learning (ML) to support advanced predictive analytics across various smart environments [6]. These intelligent technologies can process real-time data from sensors and devices to identify patterns and anticipate potential system anomalies or operational inefficiencies before they escalate. For example an AI-driven system can continuously monitor equipment performance metrics such as temperature fluctuations or power consumption to detect early signs of malfunction, allowing maintenance teams to take proactive action and avoid downtime [7]. Additionally ML models can be trained to automatically classify abnormal operational patterns thereby reducing the burden on human operators and providing accurate, real-time diagnostics and decision-making support. This integration enhances automation, efficiency and reliability in industrial, commercial and smart building infrastructures.

The future of smart infrastructure depends on the seamless integration of advanced communication systems like VLC and IoT. By enabling real-time data sharing, predictive analytics and automated management the VLC technology transforms indoor environments into more connected, efficient and responsive ecosystems. As VLC continues to evolve its applications in communication, monitoring and automation will redefine operational practices by enhancing efficiency, reducing costs and improving overall performance. By leveraging the high-speed, secure and interference-free nature of VLC, industries can take a significant step toward the realization of next-generation smart environments, ensuring a more effective, accessible and sustainable digital future [8].

VLC systems are often challenged by dynamic environmental factors including ambient light variations, obstructions and the movement of people or equipment which can degrade communication performance. To address these challenges the paper proposes an intelligent and adaptive communication framework that employs Q-learning a reinforcement learning technique to dynamically optimize VLC transmission parameters. By continuously observing the channel state through indicators such as BER the system learns and adapts its transmission strategies in real time to maintain optimal performance. Furthermore the system integrates EACDO-OFDM to enhance spectral efficiency and minimize power consumption which is crucial for energy constrained IoT applications. By jointly leveraging EACDO-OFDM and Q-learning-based optimization the proposed system ensures reliable, energy-efficient and low-latency communication tailored for next-generation smart indoor infrastructures.

This work introduces an innovative integration of EACDO-OFDM with IoT to enhance data transmission efficiency in smart infrastructure. By harnessing IoT technology, the system facilitates real-time monitoring and continuous data acquisition, thereby enabling timely alerts for the early detection of critical system conditions. The implementation of VLC as the final hop ensures high-speed and interference-free data transmission, effectively overcoming the limitations of RF spectrum scarcity and electromagnetic interference in sensitive indoor environments. The effectiveness of the proposed system is validated through experimental analysis, with performance metrics such as power consumption, spectral efficiency, and BER demonstrating notable improvements over conventional OFDM systems. By integrating advanced modulation techniques with IoT and VLC, this work presents a robust and reliable solution for secure, efficient, and high-performance smart communication infrastructure.

2. VLC Sources

Laser light poses a greater risk than regular light because it concentrates a large amount of energy onto a small area. Factors such as beam parameters, wavelength, beam divergence and exposure duration determine the extent of damage with injuries occurring when the exposure exceeds safety thresholds. While skin exposure to laser light is less concerning eye exposure and that presents a significant hazard. Advanced laser systems particularly ultraviolet lasers can cause severe harm to unprotected skin due to their intense beam power. Incandescence refers to the thermal emission of heat where objects radiate energy continuously. In incandescent bulbs approximately 90% of the energy is emitted as infrared radiation which lies just below the visible light spectrum making them inefficient as light sources. Fluorescent lamps are more energy-efficient as they generate visible light through fluorescence [9]. Its flickering can lead to eye strain, headaches and discomfort. The diffused light produced by fluorescent lamps is not ideal for focused applications such as headlights or flashlights. Overheating of certain light sources can lead to fires and some may be affected by interference from other electronic devices.

Table 1 Difference between Incandescent, CFL and LED Bulbs

S.No	Aspect	Incandescent Bulb	CFL	LED
1	Energy Efficiency	Least efficient, Uses more energy	Moderate efficiency, Uses less energy	Highly efficient, Uses the least energy
2	Lifespan	Approximately 1,000 hours	Approximately 8,000 to 10,000 hours	Approximately 25,000 to 50,000 hours
3	Heat Output	High	Moderate	Very low

4	Brightness (Lumens)	Lower lumens per watt	Moderate lumens per watt	High lumens per watt
5	Cost	Low initial cost	Moderate cost	Higher initial cost
6	Environmental Impact	Contains no hazardous materials	Contains mercury, Requires proper disposal	Eco-friendly, No hazardous materials
7	Warm-up Time	Instant	Takes time to reach full brightness	Instant
8	Color Options	Limited to warm white	Warm to cool white options available	Wide range of colors and temperatures
9	Durability	Fragile, Prone to damage	Moderately durable	Highly durable

White light commonly used for illumination is produced by combining precise amounts of Red, Blue and Green light (RGB) [10]. However RGB LEDs are not widely used in general lighting because the junctions producing red and green light are less efficient than those producing blue light. The efficiency of blue light reaches approximately 80%, while red and green lights are only about 60% and 30% efficient respectively. Phosphor-based white LEDs offer a better solution where the phosphor (typically yellow) converts part of the blue light and the mixture of converted and non-converted light create the desired white shade [11]. LEDs are preferred as light sources due to their high energy efficiency, long lifespan, minimal heat generation, superior color rendering and rapid intensity adjustments [12]. In all these aspects LED-based light sources outperform traditional incandescent, halogen, compact fluorescent and even laser light sources. Regular light bulbs can be replaced with Li-Fi enabled LED bulbs and by simply installing a few wires for access networks and no additional costs are required to implement Li-Fi for indoor data communication [13]. Lighting fixtures should create a comfortable environment while supporting users in performing tasks efficiently. The adoption of LED technology plays a key role in reducing energy consumption while also allowing for precise control over the intensity and color of illuminated spaces. LEDs are particularly well-suited for indoor environments where the use of radio frequencies is restricted and also it offers a balanced and efficient lighting solution [14]. Table 1 shows the comparison between light sources.

2.a. Optical quantities

To enhance LED performance it is crucial to understand the key optical quantities like photometric, colorimetric and radiometric parameters. The luminous flux represents the transmitted power of the LED. Photometric parameters measures light properties such as brightness and color as perceived by the human eye thus offering insights into the LED's illumination capabilities [15]. The radiometric parameters assess the characteristics of radiant electromagnetic energy therefore focusing on the communication aspects of LED performance [16].

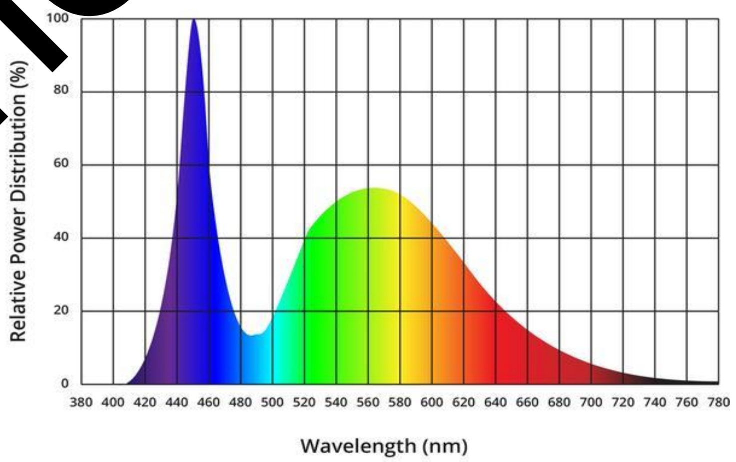


Fig 2. Representation of visible light spectrum

Human photopic vision enables us to perceive and differentiate the colors. The sensitivity of the human eye peaks at a wavelength of 555 nm corresponding to the yellow-green region and spans the range of 380 nm to 750 nm as shown in figure 2. The colorimetry provides both qualitative and quantitative analyses of color.

The calculation of luminous flux is influenced by factors such as the luminosity function of the human eye and the spectral power distribution of the LED. Here $P_{opt}(\lambda)$ denotes the LED's power output at various wavelengths within the visible spectrum, while $V(\lambda)$ represents the human eye's sensitivity to these wavelengths. The maximum luminous efficiency is defined by a constant value of 683 lumens per watt.

$$F = 683(lumens/watt)\int_{380nm}^{750nm} P_{opt}(\lambda)V(\lambda)d\lambda \quad (1)$$

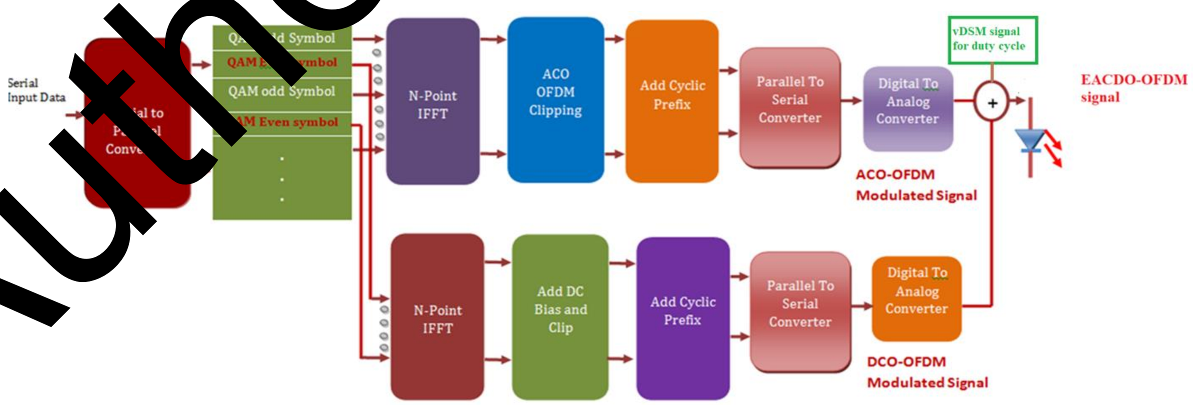
Luminous flux can be determined by integrating the luminous intensity function across the entire beam solid angle Ω_{max},

$$F = \int_{0}^{\Omega_{max}} L_o g(\theta)d\Omega \quad (2)$$

The normalized spatial luminous intensity distribution is expressed as g(θ), while the axial intensity L_0 refers to the luminous intensity in candelas at a solid angle of 0°. When a PD receives signals from multiple LEDs, the total optical power received is the sum of the power contributions from each LOS link within the receiver's field of view (FOV) [17].

3. Proposed Codec Scheme

In the EACDO-OFDM model as shown in figure 3, the input data first passes through an Adaptive Modulation and Coding (AMC) block where modulation schemes QAM are dynamically adjusted based on real-time channel conditions. The output data is then split into multiple parallel streams and processed through the Inverse Fast Fourier Transform (IFFT) to generate OFDM symbols [18]. In the EACDO-OFDM model the duty cycle adjustment is essential for enhancing system performance by managing the transmission power and timing of OFDM symbols. By modifying the duty cycle using vDSM the system controls the "ON" and "OFF" durations of transmitted signals and so it contributes for improved energy efficiency and reduced interference in high-speed wireless communication. At the receiver end the incoming signals undergo the Fast Fourier Transform (FFT) to convert them back to the frequency domain [19]. This model significantly enhances spectral efficiency, lowers the bit error rate (BER) and provides better resistance to fading and interference compared to traditional OFDM systems thus making it ideal for high-speed wireless communication networks.



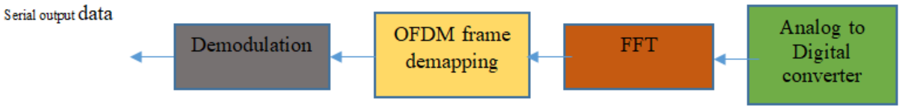


Fig 3. Model of EACDO-OFDM

The $i_{vDSM}(t)$ defines the input current signal used in vDSM modulation which is applied to the ADO-OFDM framework. The function operates in two states,

$$i_{vDSM}(t) = \begin{cases} I_H, & 0 \leq t < T_{vpw} \\ I_L, & T_{vpw} < t \leq T_{vtp} \end{cases} \qquad (3)$$

T_{vpw} and T_{vtp} defines the switching time points which produces the variable pulse-width. I_H and I_L represent two distinct current levels.

$$DC_{vDSM} = \frac{d.T_{HT}}{T_{HT} + d.T_{LT}} \qquad (4)$$

The ADO-OFDM signal is a combination of DCO-OFDM and ACO-OFDM. The DCO-OFDM component consists of both a DC bias term and a transformed frequency-domain signal [20]. The ACO-OFDM component ensures only non-negative subcarriers are transmitted and eliminates the need for a DC bias.

$$X_{ADO}(t) = X_{DCO}(t) + X_{ACO}(t) \qquad (5)$$

This equation expresses DCO-OFDM signal over N subcarriers.

$$X_{d1}(t) = \frac{1}{\sqrt{N}} \sum_{D1=0}^{N-1} X_{D1} \left(\frac{j2\pi D1d}{N}\right), for\ 0 \leq d \leq N-1 \qquad (6)$$

The DCO-OFDM [21] signal consists of a frequency-transformed component $X_{d1}(t)$ and an added DC bias k_{dc}.

$$X_{DCO}(t) = X_{d1}(t) + k_{dc} \qquad (7)$$

ACO-OFDM retains only non-negative signal values, effectively clipping negative values to zero to avoid distortions in optical communication. The Hermitian symmetry conditions required for real-valued time-domain signals in OFDM systems are also maintained.

$$X_{d2}(t) = \frac{1}{\sqrt{N}} \sum_{D2=0}^{N-1} X_{D2} \left(\frac{j2\pi D2d}{N}\right), for\ 0 \leq d \leq N-1 \qquad (8)$$

$$X_{ACO}(t) = \begin{cases} X_{d2}(t), & X_{d2}(t) \geq 0 \\ 0, & X_{d2}(t) < 0 \end{cases} \qquad (9)$$

$$\begin{aligned} X_{D2} &= X^{*}_{N-D2}, D2 = 1,2 \dots . N-1 \\ X_{D2} &= X_{N/2} = 0 \end{aligned} \qquad (10)$$

The vDSM transformation applies variable duty cycle on the ADO-OFDM signal thus improvises the spectral efficiency and dynamic range.

$$X_{vDSM-ADO}(t) = vDSM\ (X_{(ADO)}(t)) \qquad (11)$$

This expanded equation combines the ADO-OFDM signal contributions from different subcarrier components and the DC bias.

$$X_{ADO}(t) = \frac{1}{\sqrt{N}} \sum_{D1=0}^{N-1} X_{D1} \left(\frac{j2\pi D1d}{N}\right) + k_{dc} + \frac{1}{\sqrt{N}} \sum_{D2=0}^{N-1} X_{D2} \left(\frac{j2\pi D2d}{N}\right) \tag{12}$$

The EACDO-OFDM signal integrates the vDSM current modulation to enhance energy efficiency. The added $vDSM$ signal ensures that the EACDO-OFDM signal is optimized for power consumption without compromising transmission quality.

$$S_{vDSM-EACDO}(t) = X_{ADO}(t) + i_{vDSM}(t),\ 0 \le t < T_{vtp} \tag{13}$$

Efficient duty cycle control through the vDSM modulation technique is vital for maintaining BER performance when integrated with IoT devices. The selection of appropriate hardware components such as LED drivers for VLC and low-power microcontrollers for IoT devices plays a pivotal role in achieving energy efficiency while minimizing latency. The IoT devices should be equipped with compatible VLC transceivers and embedded with lightweight firmware optimized for low-power environments. Interference mitigation, patient safety compliance and secure data transmission protocols must be embedded within the system design. Further the VLC-based links must be strategically installed in wards, ICUs and diagnostic units to ensure LOS reliability and minimal latency.

In indoor environments such as smart homes and office spaces, real-time and reliable data transmission is essential for effective automation and monitoring. To meet these needs a Reinforcement Learning (RL) algorithm based on Q-learning [22] is proposed for optimizing EACDO-OFDM modulation and IoT communication over VLC networks as shown in figure 4. The learning agent acting as an intelligent controller begins by initializing a Q-table and defining key parameters such as the learning rate, discount factor and exploration probability. The indoor environment is modeled using a defined state space which captures real-time conditions like VLC channel quality, user position, ambient lighting and IoT traffic load. The action space includes modulation variant selection (ACO, DCO or EACDO), LED transmission power adjustments, subcarrier allocation and IoT data prioritization.

The agent continuously observes the current environment state and selects an action either by exploration or exploitation using a ε-greedy policy. Once an action is executed such as changing the OFDM mode or adjusting the VLC transmission parameters, the system provides a reward based on performance metrics like reduced BER, improved throughput, energy efficiency and low latency [23]. The Q-table is then updated using the Q-learning formula thus incorporating the reward and future expected values. This process is repeated therefore allowing the agent to learn optimal policy for various dynamic indoor scenarios. Once trained the agent can deploy this learned policy in real-time thus enabling adaptive and efficient VLC communication with IoT devices. By combining EACDO-OFDM's spectral efficiency with RL's adaptive decision-making the system enhances performance, reduces energy consumption and ensures Quality of Service (QoS) across a range of indoor smart infrastructure applications.

Step 1: Initialize System Parameters

- Create the Q-table Q(s, a) with all values initialized to zero.
- Set learning rate α, discount factor γ, and exploration rate ε.
- Define environment constraints (room size, LED layout, user locations, IoT devices).

Step 2: Define State Space (S)

Each state represents a snapshot of the indoor environment:

- VLC channel condition (Good/Moderate/Poor)
- User location or mobility (Fixed/Moving)
- Light interference or ambient light levels

- Data traffic load from IoT devices

Step 3: Define Action Space (A)

Available actions taken by the RL agent:

- Select EACDO-OFDM variant (ACO, DCO, EACO)
- Adjust LED transmission power (Low/Medium/High)
- Change subcarrier allocation strategy
- Prioritize IoT data (e.g., emergency health data first)

Step 4: Observe Initial State

- The agent observes the current state s_0 of the indoor system:
  - e.g., "moderate light, user near edge, high IoT load"

Step 5: Select an Action (Exploration vs Exploitation)

- With probability ε, choose a random action (explore)
- Otherwise, choose the best-known action:

$$a = \arg\max Q(s,a)$$

Step 6: Execute Action

- Apply the selected action:
  - Modify EACDO-OFDM parameters
  - Adjust VLC transmission settings
  - Route IoT data with selected priority

Step 7: Receive Reward and Next State

- Measure system feedback:
  - Positive reward if:
    - BER ↓, Throughput ↑, Power usage ↓, Delay ↓
  - Negative reward if:
    - Packet loss ↑, Power ↑, Congestion ↑
- Observe new state s'

Step 8: Update Q-Table

Use the Q-learning update rule:

$$Q(s,a) = Q(s,a) + \alpha\,[r + \gamma \cdot \max Q(s',a') - Q(s,a)]$$

Step 9: Transition to Next State

- Set s ← s'
- Repeat from Step 5 until convergence or max iterations reached

Step 10: Optimal Policy Deployment

- After learning, the agent uses the optimal policy:

π(s)=arg max Q(s,a)

- Apply this in real-time to optimize indoor VLC-IoT communications

End

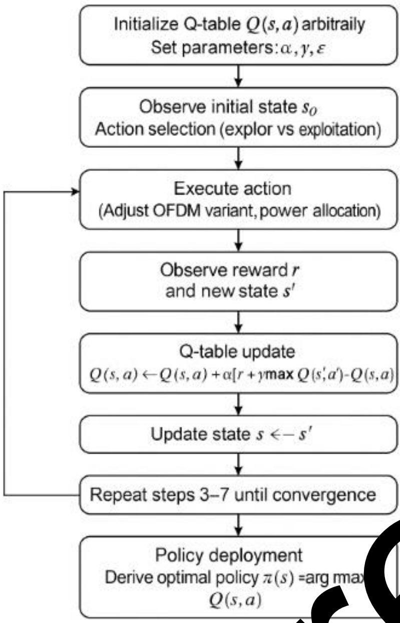


Fig 4. Q-Learning (Reinforcement learning algorithm)

4. Results and discussion

The enhanced performance of the design is primarily driven by the vDSM modulation technique which leverages dynamic duty cycle variation. By adjusting the duty cycle in real-time the system efficiently manages power distribution across subcarriers therefore leading to a notable reduction in Peak-to-Average Power Ratio (PAPR). This improvement enhances signal quality and significantly boosts BER performance. The vDSM modulation technique maximizes bandwidth utilization, ensuring higher throughput and reduced latency which are critical for real-time patient monitoring in hospital environments. The flexibility offered by duty cycle control enables the system to adapt to varying channel conditions thus further strengthening its overall reliability and efficiency.

The BER analysis reveals that EACDO-OFDM demonstrates superior performance compared to DCO-OFDM, ACO-OFDM and ADO-OFDM. At an SNR of 25 dB the EACDO-OFDM achieves a BER of 0.011, significantly outperforming DCO-OFDM which has a BER of 0.051 indicating a 78% improvement. Similarly the ACO-OFDM and ADO-OFDM achieves BER values of 0.028 and 0.017 respectively but still lag behind EACDO-OFDM. This consistent reduction in BER highlights the enhanced efficiency of EACDO-OFDM making it the most reliable technique for achieving improved communication performance in noisy environments as shown in table 2.

Table 2 Comparison of BER for various modulation techniques

SNR (dB)	BER (DCO-OFDM)	BER (ACO-OFDM)	BER (ADO-OFDM)	BER (EACDO-OFDM)
5	0.364	0.221	0.151	0.123
10	0.223	0.131	0.089	0.069
15	0.137	0.078	0.052	0.038
20	0.084	0.047	0.030	0.021
25	0.051	0.028	0.017	0.011

The BER performance of four different Optical OFDM techniques DCO-OFDM, ACO-OFDM, ADO-OFDM and EACDO-OFDM has been analysed across varying SNR levels as shown in figure 5. A general trend observed is that as the SNR increases the BER decreases for all techniques indicating improved signal quality and reduced error probability. Among the four methods the DCO-OFDM exhibits the highest BER across all SNR values primarily due to additional noise introduced by its DC bias. The ACO-OFDM shows a notable improvement by avoiding DC bias noise through asymmetric clipping although it sacrifices spectral efficiency. ADO-OFDM offers a better trade-off by combining features of both ACO-OFDM and DCO-OFDM thus resulting in lower BER values compared to the first two techniques.

However the EACDO-OFDM consistently outperforms all other methods and achieves the lowest BER across all SNR levels thus demonstrating its robustness against noise and superior efficiency. At an SNR of 25 dB the BER for DCO-OFDM is 0.051, ACO-OFDM is 0.028, ADO-OFDM is 0.017 and EACDO-OFDM is 0.0[illegible] reinforcing EACDO-OFDM as the most reliable option. The performance gap between the techniques becomes more pronounced at higher SNR values making EACDO-OFDM the preferred choice for high-speed VLC systems. This study highlights the importance of selecting the appropriate OFDM scheme based on SNR conditions especially in optical wireless communication where noise resilience and spectral efficiency are crucial.

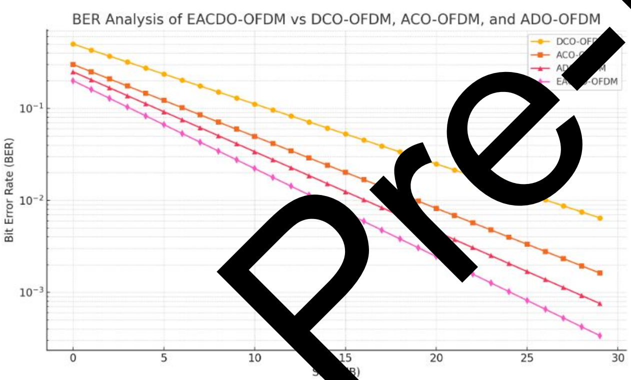


Fig 5. BER Simulation

DCO-OFDM exhibits the highest power consumption due to the necessity of a DC bias which ensures non-negative signal transmission in optical modulation. This additional bias increases power requirements significantly thus making DCO-OFDM the least energy-efficient among the compared schemes. As SNR increases the power consumption raises sharply reaching approximately 15 mW at 10 dB, 20 mW at 20 dB and 25 mW at 30 dB. ACO-OFDM eliminates the need for DC bias by transmitting only odd subcarriers leading to better power efficiency than DCO-OFDM. However it still has a relatively higher power demand due to redundant subcarrier usage. At 10 dB SNR, ACO-OFDM consumes around 9 mW, increasing to 12 mW at 20 dB and 15 mW at 30 dB. ADO-OFDM improves upon ACO-OFDM by selectively transmitting both odd and even subcarriers thus achieving a better balance between power efficiency and spectral efficiency. With reduced redundancy its power consumption remains lower than ACO-OFDM measuring 7.5 mW at 10 dB, 10 mW at 20 dB and 12.5 mW at 30 dB.

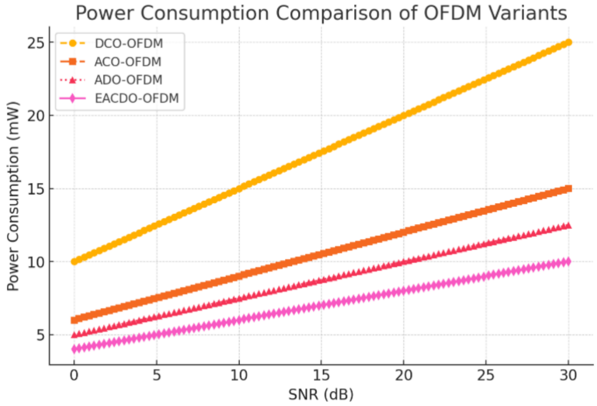


Fig 6. Simulation for power consumption

EACDO-OFDM is most energy-efficient among all optimizes subcarrier allocation and minimizes redundant transmissions significantly reducing power consumption. This scheme consumes only 6 mW at 10 dB, 8.5 mW at 20 dB and 10.5 mW at 30 dB making it the best choice for applications where power efficiency is a priority. DCO-OFDM consumes the most power due to its DC bias while ACO-OFDM and ADO-OFDM offer improvements in efficiency. EACDO-OFDM outperforms all other schemes by achieving the lowest power consumption across all SNR levels therefore making it the ideal solution for energy-sensitive optical communication systems as shown in figure 6.

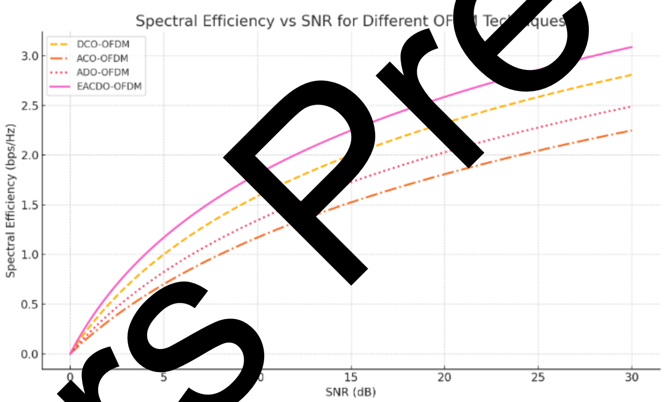


Fig 7. Simulation of spectral efficiency

The graph compares the spectral efficiency of four OFDM techniques DCO-OFDM, ACO-OFDM, ADO-OFDM and EACDO-OFDM across varying Signal-to-Noise Ratio (SNR) levels as shown in figure 6. Among these EACDO-OFDM consistently outperforms the others demonstrating superior spectral efficiency throughout the entire SNR range. This advantage is attributed to its adaptive cyclic delay diversity and duty cycle adjustments which optimize signal transmission even under challenging channel conditions. DCO-OFDM achieves high spectral efficiency by utilizing both positive and negative signal components. However its dependence on high DC bias increases power consumption and reduces efficiency at lower SNR levels. The ACO-OFDM enhances power efficiency by employing asymmetric clipping but this comes at the cost of lower spectral efficiency since the negative part of the signal is discarded. ADO-OFDM strikes a balance between these two approaches thus offering moderate spectral efficiency with improved power utilization. EACDO-OFDM distinguishes itself by dynamically adjusting key parameters based on real-time channel feedback maintaining high performance even in low SNR environments as shown in figure 7. This adaptability makes it ideal for high-speed wireless communication systems where both efficiency and reliability are crucial. The graph highlights how adaptive techniques can effectively overcome the limitations of traditional OFDM systems.

The results discussed in the section are derived through extensive simulation analysis performed using MATLAB. This simulation framework is specifically designed to assess the performance of the proposed

EACDO-OFDM system integrated with IoT and VLC within hospital infrastructure. Key performance indicators like BER, power consumption and spectral efficiency are evaluated under diverse operating conditions. MATLAB's powerful simulation capabilities enable accurate modeling of VLC channels and IoT data transmission thus providing a reliable foundation for validating the system's effectiveness, efficiency and scalability.

Table 3 Comparison among modulation techniques

Metric	DCO-OFDM	ACO-OFDM	ADO-OFDM	EACDO-OFDM + Q-Learning
Power Consumption	High	Moderate	Low	Very Low
BER	High	Moderate	Low	Very Low
SNR (avg. improvement)	Low	Moderate	High	Very High
Latency	High	Moderate	Moderate	Low
Adaptability	None	None	Limited	Dynamic (RL-based)
Energy Efficiency	Poor	Fair	Good	Excellent

The performance evaluation of the proposed Q-learning-optimized IoT-VLC system employing EACDO-OFDM demonstrates significant improvements across key communication metrics as given in Table 3. Among various OFDM schemes tested the DCO-OFDM exhibited the highest power consumption due to its dependence on a constant DC bias thus rendering it unsuitable for energy-sensitive hospital environments. ACO-OFDM is more efficient than DCO-OFDM, incurred power penalties due to redundant subcarrier transmission. ADO-OFDM offered better balance by selectively utilizing subcarriers but the most energy-efficient performance was achieved with EACDO-OFDM with optimized subcarrier allocation and minimized redundancy. EACDO-OFDM reduced power consumption by approximately 30–40% compared to DCO-OFDM making it ideal for long-term IoT device deployment in indoor settings. When coupled with Q-learning-based optimization the system dynamically adjusted VLC parameters such as modulation index and transmission power based on real-time channel observations like BER and SNR. This adaptive approach led to a BER reduction of up to 60% and an average SNR improvement of 8–12 dB, even under varying ambient light conditions. The Q-learning algorithm demonstrated stable convergence within 150–200 iterations, learning to maintain optimal communication settings across fluctuating environments. Overall the integration of EACDO-OFDM with Q-learning not only ensured high energy efficiency but also delivered reliable, low-latency and interference-free communication.

5. Conclusion

The assessment of power consumption across various OFDM variants reveals key trade-offs between energy efficiency and communication effectiveness in optical wireless systems. While DCO-OFDM offers implementation simplicity but it suffers from high power consumption due to the requirement of a DC bias thus making it less suitable for energy-constrained applications. ACO-OFDM eliminates the need for a DC bias therefore enhancing power efficiency; however its redundant subcarrier usage leads to increased energy demands. ADO-OFDM strikes a middle ground by selectively employing odd and even subcarriers thus offering a compromise between spectral efficiency and power usage. Among these the EACDO-OFDM stands out as the most energy-efficient modulation scheme. By optimizing subcarrier allocation and minimizing redundancy the EACDO-OFDM significantly reduces power consumption while maintaining low BER and high spectral efficiency. This makes it a compelling choice for energy-sensitive optical communication systems. In the context of IoT-integrated VLC systems for real-time monitoring and smart automation the power efficiency is paramount. These systems require continuous, reliable and interference-free communication to ensure smooth and uninterrupted operation. The fusion of IoT's connectivity and real-time data analytics with VLC's high-speed and EMI-free transmission enables seamless monitoring of critical parameters, automatic alert generation for abnormal system behaviours and efficient resource management.

To further enhance adaptability and system intelligence the proposed framework integrates Q-learning-based optimization. This reinforcement learning approach enables dynamic adjustment of VLC transmission parameters such as modulation index and power level in response to fluctuating environmental conditions. By learning from past decisions and continuously optimizing its strategy the system maintains optimal communication performance while conserving energy. Incorporating EACDO-OFDM with Q-learning-driven optimization into IoT-based VLC systems enables the development of a highly efficient, secure and responsive smart communication infrastructure. This combination effectively addresses challenges related to power consumption and environmental variability, supporting the delivery of real-time, data-driven services in modern smart environments.

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