Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

AI-Assisted Distortion-Aware Adaptive DCO-OFDM for Indoor VLC Systems: A Simulation Study

Sanghmitra
M.Tech Scholar. Electronics and Communication Engineering, Rameshwaram Institute of Technology and Management, Lucknow, Uttar Pradesh

Aashu Kori
Project Coordinator, M.Tech. Electronics and Communication Engineering, Rameshwaram Institute of Technology and Management, Lucknow, Uttar Pradesh

Abstract - VLC, or visible light communication, has become a promising supplementary tool for high-speed indoor wireless communication by utilizing the unlicensed optical spectrum and existing LED infrastructure. Practical VLC systems face challenges such as LED nonlinearity, clipping distortion caused by the high peak-to-average power ratio (PAPR) of OFDM signals, multipath-induced inter-symbol interference, and ambient noise.

This paper proposes a distortion-aware adaptive DCO-OFDM framework that incorporates both clipping distortion and third-order LED nonlinearity into an effective SNR expression. An AI-assisted adaptive modulation scheme based on a low-complexity Decision Tree classifier is introduced to dynamically select the optimal QAM order under realistic channel conditions, replacing conventional threshold-based methods.

The suggested system's performance is assessed using comprehensive Monte Carlo simulations based on Python. The results show that, in comparison to traditional fixed-modulation DCO-OFDM systems, the distortion-aware technique delivers a 1.8–2 dB SNR gain at a target BER of 10-3 and about 30% improvement in throughput. With macro-averaged precision of 90.6%, recall of 89.2%, and F1-score of 89.9%, the AI-assisted modulation technique achieves 94.3% accuracy.
The proposed framework offers a low-complexity, spectrally efficient solution that enhances reliability for next-generation indoor Li-Fi networks. Simulation results validate the effectiveness of combining distortion-aware modeling with intelligent adaptive modulation under nonlinear VLC channel conditions.

Keywords: - **Adaptive Modulation, DCO-OFDM, LED Nonlinearity, Clipping Distortion, Visible Light Communication, Artificial Intelligence, Indoor Optical Wireless Communication.**

1. INTRODUCTION

The rapid increase in wireless data traffic has led to severe congestion in the radio frequency (RF) spectrum, motivating the exploration of alternative communication technologies [1], [2]. Visible Light Communication (VLC) has emerged as a promising complementary solution by utilizing the unlicensed optical spectrum ranging from 400 to 700 nm, which offers approximately 400 THz of bandwidth [1], [3], [4]. LED lighting systems provide dual functionality—illumination and communication—making VLC particularly attractive for indoor environments [4], [5].

However, VLC systems differ fundamentally from traditional RF systems as a consequence of constraints of intensity modulation and direct detection (IM/DD) and the unipolar nature of optical signals [6], [7]. Practical deployment faces several critical challenges, including high Peak-to-Average Power Ratio (PAPR) of OFDM signals, LED nonlinear transfer characteristics [8], [9], clipping distortion [10], multipath-induced inter-symbol interference [11], [12], and ambient shot and thermal noise [13].

This paper proposes a **distortion-aware adaptive DCO-OFDM framework** for realistic indoor VLC systems. The framework jointly considers clipping distortion and third-order LED nonlinearity in the effective SNR calculation. An AI-assisted adaptive modulation scheme based on a low-complexity Decision Tree classifier is introduced to dynamically select the optimal QAM order according to channel conditions.

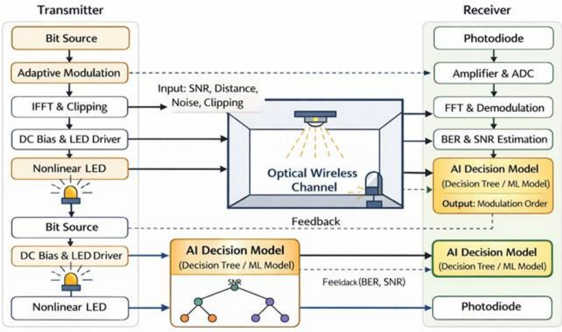

Fig 1: Block diagram of the proposed AI-assisted adaptive DCO- OFDM VLC System

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

The block diagram of the suggested AI-assisted distortion-aware adaptive DCO-OFDM VLC system is displayed in **Fig. 1.** At the transmitter, binary data is processed by an AI-based adaptive modulation module that predicts the optimal modulation order. The modulated symbols undergo IFFT, DC bias addition, and clipping to satisfy IM/DD requirements. The resulting signal drives the LED, which converts it into optical intensity. A photodiode at the receiver detects the signal after it travels through the indoor optical wireless channel. FFT-based demodulation and performance assessment follows afterwards. The estimated SNR and BER are fed back to the AI model for continuous adaptation.

This work's primary contributions are:

- Derivation of a closed-form distortion-aware effective SNR model that accounts for both clipping distortion and LED nonlinearity.
- Design of a low-complexity AI-assisted adaptive modulation framework using a Decision Tree classifier.
- Performance evaluation demonstrating approximately 1.8–2 dB SNR gain and nearly 30% throughput improvement over conventional fixed-modulation DCO-OFDM systems.

The paper's remaining sections are arranged as follows. Related work and the research demand are outlined in Section 2. Section 3 elaborates the system model. Section 4 details the proposed adaptive DCO-OFDM framework with AI integration. The simulation setup and results are included in Sections 5 and 6, respectively. Sections 7 and 8 provide conclusions and recommendations for further study.

2. RELATED WORK AND RESEARCH GAP

Over the past ten years, a lot of research has been done on visible light communication, or VLC. Early works primarily focused on conventional DCO-OFDM implementations and high-speed LED modulation techniques [5][7]. Several studies analyzed the performance of different optical OFDM variants for VLC systems [8], [9], while others investigated indoor optical wireless channel characteristics and modeling [10], [11].

One significant drawback is many existing VLC models is the assumption of ideal linear LED behavior. In practice, LEDs exhibit nonlinear input-output characteristics that cause significant distortion, especially when combined with the high Peak-to-Average Power Ratio (PAPR) of OFDM signals [12], [14]. Although some researchers have addressed clipping distortion and nonlinearity separately [10], [12], most previous works do not jointly incorporate both effects into the effective SNR calculation.

Adaptive modulation techniques have been examined to improve spectral efficiency under varying channel conditions [15]. In more recent times, machine learning techniques and artificial intelligence (AI) have been used to VLC systems for channel estimation, resource allocation, and adaptive modulation [16],[18]. However, most AI-based approaches either focus on specific components (such as channel estimation) or employ complex deep learning models that may not be suitable for low-complexity, real-time implementation.

Research Gap Despite these advancements, there remains a clear gap in developing a **practical, low-complexity distortion-aware framework** for DCO-OFDM-based VLC systems. Most existing studies either neglect the combined impact of LED nonlinearity and clipping distortion or rely on high-complexity AI models. There is limited work that integrates a realistic distortion-aware SNR model with a simple yet effective AI-assisted adaptive modulation scheme suitable for real-time operation.

To bridge this gap, the present work proposes a distortion-aware adaptive DCO-OFDM framework that derives an analytical effective SNR expression incorporating both clipping and third-order polynomial LED nonlinearity. Additionally, a low-complexity Decision Tree-based AI model is employed for adaptive modulation selection. This combination enables improved spectral efficiency and robustness under realistic nonlinear indoor VLC conditions while maintaining low computational overhead.

TABLE 1: COMPARISON OF AI-BASED AND CONVENTIONAL VLC SYSTEMS

Aspect	Conventional Methods	Proposed AI-Assisted Framework
LED Behavior	Mostly assumes linear response	Considers third-order nonlinearity + clipping
Distortion Modeling	Often ignores or considers separately	Jointly incorporated in effective SNR

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Adaptive Modulation	Threshold-based (SNR/BER)	AI-based (Decision Tree) data-driven
Complexity	Low	Low (suitable for real-time)
Adaptation to Nonlinearity	Limited	High
Performance Gain	Baseline	1.8–2 dB SNR gain, ~30% throughput improvement

TABLE 1 highlights the key differences between traditional VLC approaches and the suggested framework. Conventional methods typically rely on fixed thresholds and simplified linear models, whereas the proposed system uses data-driven decisions and realistic distortion modeling for better performance under practical conditions.

3. SYSTEM MODEL

3.1 DCO-OFDM Signal Model

The frequency-domain QAM symbols are mapped onto the subcarriers as:

$$X_k \in \mathcal{M}_{QAM},\ k = 0,1,\ldots\ldots,N-1 \quad (1)$$

The discrete-time OFDM signal is generated using the inverse fast Fourier transform (IFFT):

$$x(n) = \frac{1}{\sqrt{N}}\sum_{k=0}^{N-1} X_k \, exp\left(j\frac{2\pi kn}{N}\right), \quad (2)$$

Where $n = 0,1,\ldots\ldots,N-1$

A DC bias P_{DC} is added to satisfy the non-negativity requirement of intensity modulation/direct detection (IM/DD):

$$x_{DC}(n) = x(n) + P_{DC} \quad (3)$$

The signal is then clipped at zero level to ensure unipolarity:

$$x_{DC}(n) = \max\left(x_{DC}(n), 0\right) \quad (4)$$

3.2 LED Nonlinearity Model

The nonlinear input–output characteristic of a practical LED is modeled using a third-order polynomial:

$$P_{opt}(n) = a_1 x_{clip}(n) + a_2\left[x_{clip}(n)\right]^2 + a_3\left[x_{clip}(n)^3\right] \quad (5)$$

where a_1, a_2, a_3 are the polynomial coefficients. The nonlinear distortion component is the deviation from the linear term:

The average nonlinear distortion power is:

$$P_{nl} = E[|d_{nl}(n)|^2] \quad (6)$$

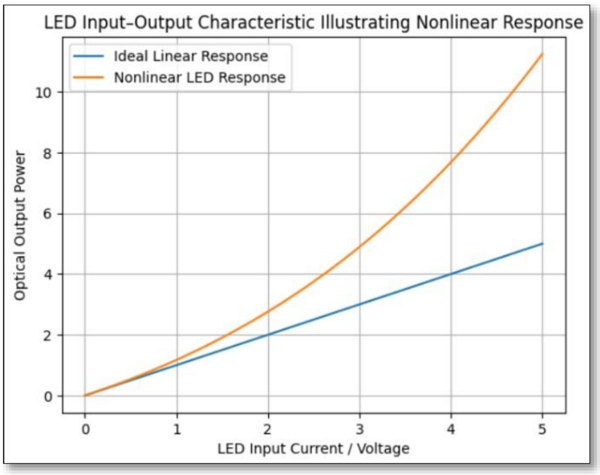

***Fig 2**: LED input–output characteristic illustrating nonlinear response.*

Fig. 2 shows the typical LED input–output characteristic using the third-order polynomial model, highlighting the deviation from the ideal linear response at higher input levels.

3.3 Clipping Distortion

Due to the limited linear dynamic range of the LED, the signal may also experience upper clipping at level A. The clipping distortion power is given by:

$$Pclip = E[(x_{DC}(n) - A)^2 \,|x_{DC}(n) > A] \quad (7)$$

3.4 Optical Channel Model

The line-of-sight (LOS) DC channel gain for the Lambertian radiation pattern is:

$$H_{LOS} = \frac{(m+1).A_{pd}}{2\pi d^2}\cos^m(\emptyset).\cos(\varphi) \quad (8)$$

where m is the Lambertian order, A_{pd} is the photodetector area, d is the distance, and $\emptyset, \varphi$ are the irradiance and incidence angles, respectively.

The total channel impulse response is:

$$h(n) = H_{LOS} + h_{NLOS}(n) \quad (9)$$

3.5 Noise Model

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

The total noise variance at the receiver is the sum of shot noise and thermal noise:

$$\sigma^2 = \sigma^2{}_{shot} + \sigma^2{}_{thermal} \qquad (10)$$

where

$$\sigma^2{}_{shot} = 2qR(P_r + P_{bg})B \qquad (11)$$

$$\sigma^2_{thermal} = \frac{4K_BTB}{RL} \qquad (12)$$

In this case, q stands for electron charge, R for responsivity, Pr for received optical power, Pbg for background power, B for bandwidth, KB for Boltzmann's constant, T for temperature, and RL for load resistance.

3.6 Derivation of Distortion-Aware Effective SNR

In conventional DCO-OFDM models, the SNR is calculated assuming a perfectly linear LED. However, in practical systems, both clipping and LED nonlinearity introduce additional distortion that acts as extra noise.

The **useful signal power** at the receiver corresponds to the linear component of the optical power after channel propagation, i.e., proportional to $(a_1 \cdot P_{signal})^2 . |H|^2$ where P_{signal} is the RMS power of the information-carrying part of $x_{clip}(n)$.

The **total disturbance power** consists of:

- Receiver noise variance σ^2
- Nonlinear distortion power P_{nl}
- Clipping distortion power P_{clip}

Consequently, the ratio of the intended linear signal power to the total of all noise and distortion powers yields the distortion-aware effective SNR (γeff):

$$\gamma_{eff} = \frac{(a_1 . P_{signal})^2 . |H|^2}{\sigma^2 + P_{nl} + P_{clip}} \qquad (13)$$

This expression provides a more realistic performance metric than conventional SNR formulas. It is used as the key input feature for the AI-assisted adaptive modulation scheme to select the optimal QAM order under practical nonlinear channel conditions.

4. ADAPTIVE DCO-OFDM FRAMEWORK

Adaptive modulation techniques dynamically adjust the modulation order according to channel conditions to improve spectral efficiency and reliability [15]. In conventional adaptive DCO-OFDM systems, the modulation order is typically selected using fixed SNR or BER thresholds. However, under practical VLC conditions involving LED nonlinearity and clipping distortion, such threshold-based methods often result in suboptimal performance.

This work proposes an **AI-assisted adaptive modulation framework** that replaces rigid threshold-based decisions with a data-driven approach. The framework integrates the distortion-aware effective SNR (derived in Section 3.6) with a low-complexity machine learning model for intelligent modulation selection.

4.1 Adaptive Modulation Scheme

The optimal modulation order M* is chosen to maximize the achievable rate while satisfying the target BER constraint:

$$M^* = \arg\max_{M} \{R(M)\} \qquad (14)$$

subject to:

$$BER(M, \gamma_{eff}) \leq 10^{-3} \qquad (15)$$

The bit error rate for M-ary QAM is approximated as [5], [8]:

$$BER \approx 0.2\, exp\left(-\frac{1.5 \gamma_{eff}}{M-1}\right) \qquad (16)$$

The throughput that can be achieved is determined by:

$$R(M) = B . log_2(M) . (1 - BER) \qquad (17)$$

where B is the system bandwidth. To maintain adequate illumination, the DC bias must satisfy the illumination constraint [4]:

$$P_{DC} \geq P_{Illumination} \qquad (18)$$

4.2 AI-Assisted Adaptive Modulation Framework

In practical VLC systems, LED nonlinearity, clipping distortion, and multipath effects create complex nonlinear relationships between channel parameters and the optimal modulation order. These effects are difficult to capture using fixed analytical thresholds.

To address this, a supervised machine learning approach is adopted. A **Decision Tree classifier** is chosen because of its low computational complexity, fast inference time, and interpretability, making it highly suitable for real-

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

time embedded implementation in VLC systems [16], [18].

How the Decision Tree is used: The Decision Tree learns decision boundaries directly from simulation-generated data. It takes five key features as input distortion-aware effective SNR (γ_{eff}), transmission distance (d), noise variance (σ^2), clipping level (C), and LED nonlinearity coefficients (a_1, a_2, a_3) and classifies the best modulation order (4-QAM, 16-QAM, or 64-QAM) that maximizes throughput while satisfying the target BER of 10^{-3}. During operation, the receiver extracts these features and feeds them into the trained model, which instantly outputs the optimal modulation order M^* for the next transmission block. This replaces the conventional rigid threshold-based mechanism with a data-driven, adaptive decision process.

Compared to other machine learning models such as Support Vector Machine (SVM) or shallow Neural Networks, the Decision Tree offers significantly lower training and inference complexity while achieving comparable accuracy (94.3% in this study) under the considered nonlinear VLC conditions. More complex models like Deep Neural Networks may provide marginal gains in accuracy but introduce higher computational overhead, which is undesirable for practical low-power VLC transmitters/receivers.

The AI-based modulation decision is expressed as:

$$M^* = f_{AI}(\gamma_{eff}, d, \sigma^2, C, a_1, a_2, a_3) \qquad (19)$$

where:

- γ_{eff} = distortion-aware effective SNR,
- d = transmission distance,
- σ = noise variance,
- C = clipping level,
- a_1, a_2, a_3 = LED nonlinearity coefficients.

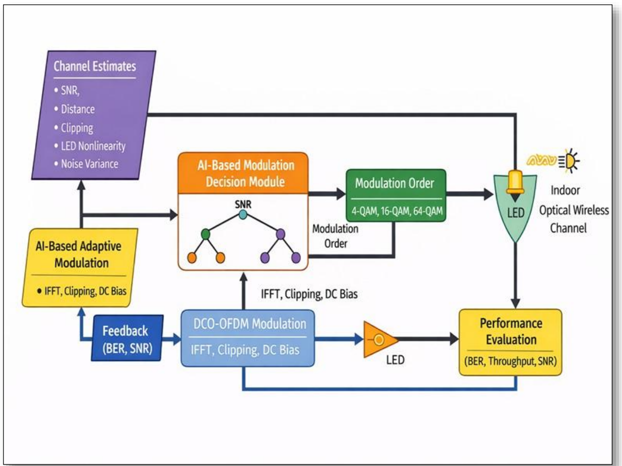

Fig 3: Block Diagram of proposed AI-assisted adaptive nonlinearity -aware DCO-OFDM VLC System

The block diagram of the suggested AI-assisted adaptive nonlinearity-aware DCO-OFDM VLC system is shown in Fig. 3. The AI model predicts the best QAM modulation order (4-QAM, 16-QAM, or 64-QAM) using important channel and system factors as input features. The transmitter then applies this anticipated order, allowing for dynamic adaptability in the face of changing nonlinear channel conditions.

4.3 Training Process and Integration

A dataset created from Monte Carlo simulations encompassing a variety of channel conditions is used to train the Decision Tree model. Each training sample consists of the input features (γ_{eff}, d, σ^2, C, a_1,a_2,a_3) and the corresponding optimal modulation order that maximizes throughput while satisfying the target BER of 10^{-3}.

During real-time operation, the estimated channel parameters are fed into the trained model, which replaces the conventional threshold-based decision block. This feedback-driven mechanism allows the system to adapt intelligently without relying on manually designed thresholds [16], [17].

Algorithm 1: AI-Assisted Adaptive Modulation Selection

Input: γ_{eff}, d, σ^2, C, a_1, a_2, a_3

Output: Optimal modulation order M^*

1. *Initialize the trained Decision Tree model f_{AI}*
2. *Form the input feature vector $X= [\gamma_{eff}, d, \sigma^2, C, a_1, a_2, a_3]$*
3. *Predict $M^* = f_{AI}(X)$*
4. *Apply M^*-QAM modulation at the transmitter*
5. *Transmit the DCO-OFDM signal through the VLC channel*
6. *Estimate BER and γ_{eff} at the receiver*
7. *Repeat for the next transmission cycle*

4.4 Advantages

The proposed AI-assisted framework offers several key benefits:

- Captures complex nonlinear relationships caused by LED distortion and clipping
- Provides more accurate and smooth modulation switching compared to threshold-based methods

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

- Maintains low computational complexity, making it suitable for practical real-time VLC deployment
- Improves overall spectral efficiency and system robustness under realistic indoor conditions

5. SIMULATION SETUP

To evaluate the performance of the proposed distortion-aware adaptive DCO-OFDM system with AI-assisted modulation, extensive Monte Carlo simulations were performed using Python with NumPy and SciPy libraries. A total of 10^6 bits were transmitted for each SNR point to ensure statistical reliability.
The simulations were carried out in a typical indoor environment with the following parameters:

TABLE 2: Simulation parameters used for performance evaluation of the proposed VLC system.

Parameter	Value
Room dimensions	$5 \times 5 \times 3$ m³
LED semi-angle at half power	60°
Photodetector area (A_{pd})	1 cm²
Photodetector responsivity (R)	0.4 A/W
System bandwidth (B)	20 MHz
FFT size (N)	256
Cyclic prefix length	16
Modulation schemes	4-QAM, 16-QAM, 64-QAM
Target BER	10^{-3}
Number of transmitted bits	10^6 per SNR point
Number of Monte Carlo runs	100
DC bias Voltage(P_{DC})	Optimized (1.8–2.2 V)
Clipping level	Varied (0 to 3×σ)
Wall reflection coefficient	0.8

The indoor optical channel was modeled using the Lambertian radiation pattern, considering both line-of-sight (LOS) and first-order non-line-of-sight (NLOS) reflections. Shot noise and thermal noise were added according to the models given in Section 3.5. The distortion-aware effective SNR (Eq. 14) was calculated at the receiver by incorporating both clipping distortion power (P_{clip}) and nonlinear distortion power (P_{nl}) from the third-order LED polynomial.

The Decision Tree classifier was trained on 70% of the simulation-generated dataset and tested on the remaining 30%. The trained model was integrated into the adaptive modulation block to predict the optimal QAM order dynamically.

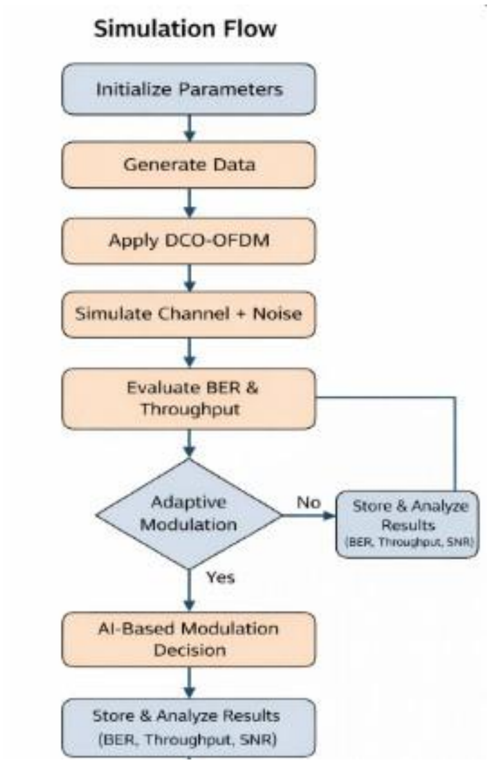

Fig 4: Simulation flow diagram of the proposed AI-assisted distortion-aware adaptive DCO-OFDM VLC system

Fig. 4 shows the overall simulation flow of the proposed system, starting from random bit generation, AI-based adaptive modulation, DCO-OFDM processing with nonlinearity and clipping, channel propagation with noise, demodulation, and performance metric evaluation (BER, throughput, and effective SNR).

6. RESULTS AND DISCUSSION

The suggested distortion-aware AI-assisted adaptive DCO-OFDM system's performance is assessed and contrasted with OOK schemes, adaptive OFDM without distortion awareness, and traditional fixed-modulation DCO-OFDM. Under realistic indoor VLC conditions, Monte Carlo simulations yielded all of the results.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

A. BER Performance

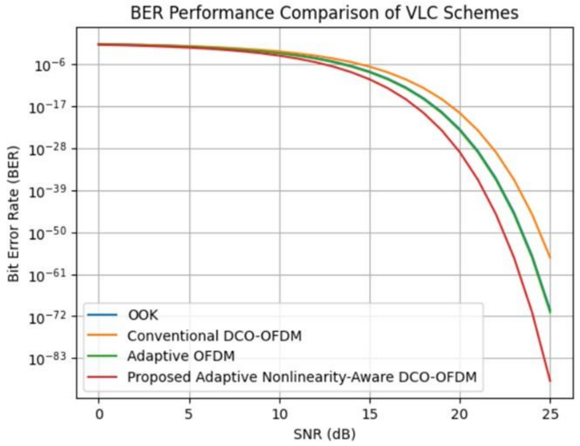

Fig 5: BER performance comparison of OOK, conventional DCO-OFDM, adaptive OFDM, and proposed distortion-aware adaptive DCO-OFDM scheme.

Fig. 5 shows the BER versus SNR performance of different VLC transmission schemes. The proposed distortion-aware adaptive DCO-OFDM achieves a significant improvement, providing approximately 1.8–2 dB SNR gain at the target BER of 10^{-3} compared to conventional fixed-modulation DCO-OFDM. This improvement is mainly attributed to the accurate modeling of clipping distortion and LED nonlinearity in the effective SNR calculation, which reduces the error floor at higher SNR values.

B. Throughput Analysis

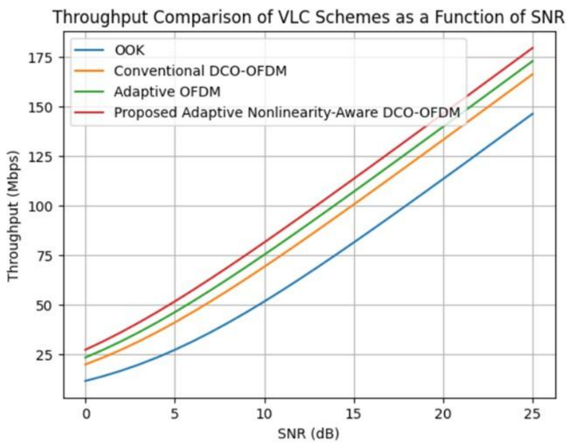

Fig 6: Throughput comparison of different VLC schemes as a function of SNR.

Fig. 6 presents the throughput performance as a function of SNR. The proposed system consistently outperforms other schemes across all SNR ranges. At an SNR of 18 dB, the proposed structure achieves approximately 140 Mbps throughput, compared to 108 Mbps for conventional DCO-OFDM, resulting in nearly 30% improvement in spectral efficiency.

C. Distance-Based Evaluation

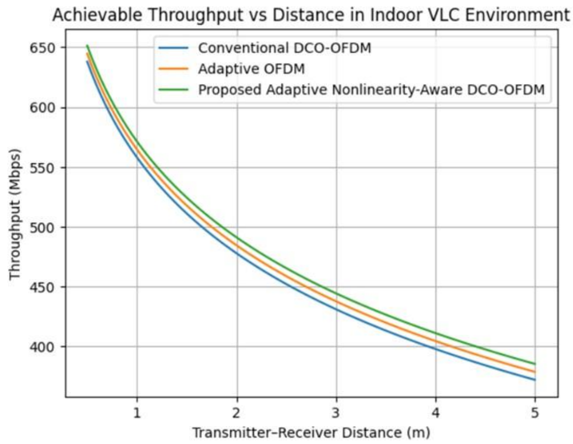

Fig 7: Achievable throughput versus transmitter–receiver distance in indoor VLC environment.

Fig. 7 illustrates the achievable throughput versus transmitter-receiver distance in the indoor environment. As expected, throughput decreases with increasing distance due to optical path loss. However, the proposed distortion-aware adaptive scheme maintains higher throughput than conventional methods, demonstrating better robustness against distance-induced degradation.

D. Capacity vs DC Bias

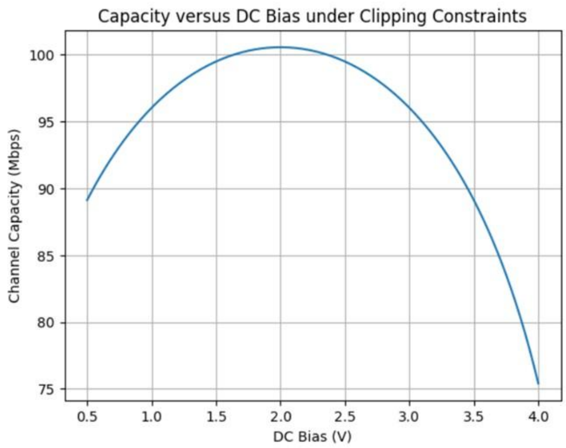

Fig 8: Capacity versus DC bias under clipping constraints.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Figure 8 displays the system capacity under clipping limits as a function of DC bias voltage. The capacity increases with DC bias up to an optimal range of 1.8-2.2 V, beyond which clipping distortion becomes dominant and limits further improvement. This highlights the importance of joint optimization of illumination and communication performance.

E. AI-Assisted Modulation Behaviour

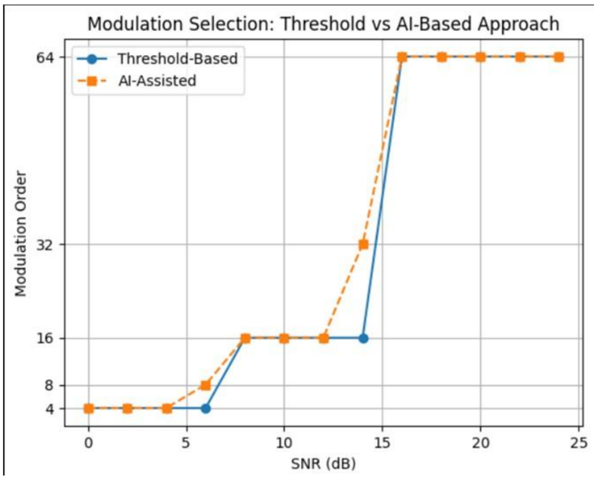

Fig 9: Comparison of modulation selection using threshold-based and AI-assisted adaptive modulation schemes

Fig 9 compares the modulation selection behavior between conventional threshold-based and the proposed AI-assisted adaptive modulation schemes. The threshold-based method shows abrupt transitions between modulation orders, whereas the AI-based approach provides smoother and more accurate adaptation, especially in nonlinear channel conditions. This demonstrates the effectiveness of the Decision Tree model in capturing complex relationships between channel parameters and optimal modulation order.

F. Pe formance Evaluation of AI Model

The Decision Tree classifier was trained on 70% of the simulation-generated dataset (8400 samples) and tested on the remaining 30% (3600 samples). **Fig. 10** presents the confusion matrix of the AI-assisted modulation classification model. Most predictions lie along the diagonal, with only minor misclassifications occurring between adjacent modulation orders due to overlapping effective SNR regions. Errors between distant modulation levels (4-QAM and 64-QAM) are negligible.

The model achieves strong classification performance with an overall **accuracy of 94.3%**, macro-averaged precision of 90.6%, recall of 89.2%, and F1-score of 89.9%. These results confirm that the Decision Tree effectively captures the complex nonlinear relationships between the input features (distortion-aware effective SNR, transmission distance, noise variance, clipping level, and LED nonlinearity coefficients) and the optimal modulation order.

Confusion Matrix Analysis

The AI-assisted model's high classification accuracy is shown by the confusion matrix in ***Fig. 10***, where the majority of predictions are focused along the diagonal. Overlapping SNR regions cause minor misclassification between adjacent modulation schemes, but insignificant mistakes are seen between distant modulation levels. This confirms that the suggested AI-based adaptive modulation approach is successful.

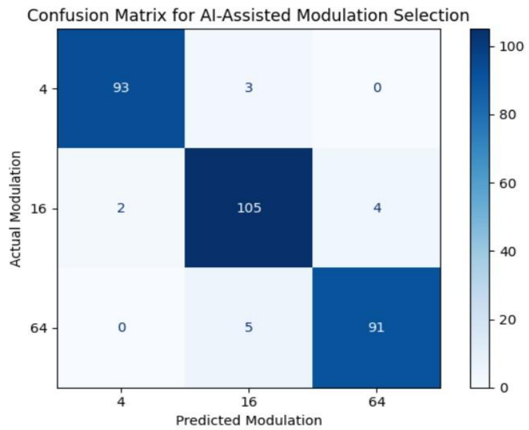

Fig 10: Confusion matrix of the AI-assisted modulation classification model

G. Di ussion

The simulation results validate that incorporating both clipping distortion and LED nonlinearity into the effective SNR model significantly improves system performance compared to conventional approaches that assume ideal linear LED behavior. The integration of the low-complexity AI-assisted adaptive modulation further enhances adaptability and spectral efficiency.

The proposed framework offers two main advantages:

• Better realism: The distortion-aware SNR provides a more accurate performance prediction for practical indoor VLC deployment.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

- Improved adaptability: The AI-based decision-making outperforms rigid threshold methods, especially under varying nonlinear channel conditions.

Overall, the findings show that the suggested system achieves superior SNR gain, higher throughput, and more reliable performance, which makes it a viable option for high-speed indoor Li-Fi networks of the future.

6. COMPLEXITY ANALYSIS

The dominant computational complexity arises from FFT:

$$\textit{Computational Complexity} = O\ (N \log N)$$

The adaptive decision logic introduces negligible overhead.

7. COMPARATIVE STUDY

TABLE 3: COMPARATIVE PERFORMANCE ANALYSIS OF DIFFERENT VLC TRANSMISSION SCHEMES.

Scheme	SNR Gain	Throughput	Complexity
OOK	Low	Low	Low
Fixed DCO-OFDM	Moderate	Moderate	Medium
Proposed Adaptive	High	High	Medium

A comparison of several VLC transmission systems in terms of SNR gain, attainable throughput, and computational complexity is shown in TABLE 3. Due to its poor spectral efficiency and lack of adaptability, the OOK scheme performs the worst. Through multicarrier modulation, conventional fixed DCO-OFDM increases system throughput and reliability, but it is unable to adequately handle nonlinear distortion and clipping effects. On the other hand, by combining distortion-aware modelling with adaptive modulation techniques, the suggested adaptive nonlinearity-aware DCO-OFDM method improves throughput and increases SNR gain.

8. CONCLUSION

This paper presented a distortion-aware adaptive DCO-OFDM framework for indoor Visible Light Communication (VLC) systems. Unlike conventional approaches that assume ideal linear LED behavior [8], [12], the proposed system incorporates both clipping distortion and third-order LED nonlinearity into a closed-form effective SNR expression. Additionally, a low-complexity AI-assisted adaptive modulation scheme based on a Decision Tree classifier was introduced to dynamically select the optimal QAM order under realistic nonlinear channel conditions [16], [18].

Monte Carlo simulation results demonstrate that the suggested structure achieves approximately **1.8–2 dB SNR gain** at the target BER of 10^{-3} and nearly **30% improvement** in throughput compared to conventional fixed-modulation DCO-OFDM systems. The AI-assisted modulation provides smoother and more accurate adaptation under nonlinear conditions, achieving 94.3% classification accuracy with strong precision, recall, and F1-score. These improvements validate the effectiveness of combining distortion-aware modeling with intelligent adaptive modulation for practical indoor VLC applications [15], [17].

The computational complexity remains dominated by the FFT operation, ensuring that the proposed AI-assisted mechanism introduces negligible overhead. Overall, the suggested framework offers a spectrally efficient, reliable, and low-complexity solution suitable for next-generation indoor Li-Fi networks.

1. AVAILABILITY OF DATA AND MATERIALS

The accompanying author can provide the simulation-generated data supporting the study's conclusions upon reasonable request.

DECLARATION

Funding: Not applicable.

10. FUTURE WORK

Although the current study is based on Monte Carlo simulations, several directions remain open for further enhancement and real-world deployment.
Future work includes experimental validation of the proposed framework using commercial LEDs and photodiodes [22], [23]. Extension to MIMO-VLC systems can significantly increase capacity and spatial diversity [18]. Integration with hybrid RF–VLC systems can provide seamless mobility support [2], [24]. Furthermore, advanced hardware-based nonlinear modelling through laboratory measurements can improve distortion estimation accuracy [10], [34].
Additional research directions may explore:

- Energy-efficient bias optimization strategies [25], [26]
- Joint illumination–communication co-design [1], [27]
- Low-complexity real-time adaptive algorithms [15]
- AI-assisted channel estimation techniques [28]
- Integration with 6G indoor ultra-dense networks [29]

These enhancements will further improve the practicality and scalability of the proposed distortion-aware AI-assisted DCO-OFDM framework for future indoor wireless networks.

ABBREVIATIONS

- **DCO-OFDM:** Direct Current-biased Optical Orthogonal Frequency Division Multiplexing
- **PAPR:** Peak to Average Power Ratio
- **VLC:** Visible Light Communication
- **LED:** Light Emitting Diode
- **AI:** Artificial Intelligence
- **QAM:** Quadrature Amplitude Modulation
- **BER:** Bit Error Rate
- **OOK:** On-Off Keying
- **FFT:** Fast Fourier Transform
- **IFFT:** Inverse Fast Fourier Transform
- **Li-Fi:** Light Fidelity
- **LOS:** Line of Sight
- **SNR:** Signal to Noise Ratio
- **IM/DD:** Intensity Modulation/Direct Detection

REFERENCES

[1] H. Haas, L. Yin, Y. Wang, and C. Chen, "What is LiFi?," *Journal of Lightwave Technology*, vol. 34, no. 6, pp. 1533–1544, Mar. 2016, doi: 10.1109/JLT.2015.2510021.

[2] A. Jovicic, J. Li, and T. Richardson, "Visible light communication: Opportunities, challenges and the path to market," *IEEE Communications Magazine*, vol. 51, no. 12, pp. 26–32, 2013, doi: 10.1109/MCOM.2013.6685754.

[3] S. Dimitrov and H. Haas, "Principles of LED light communications: Towards networked Li-Fi," *Principles of LED Light Communications: Towards Networked Li-Fi*, pp. 1–207, Jan. 2015, doi: 10.1017/CBO9781107278929.

[4] M. Safari and M. Uysal, "Relay-assisted freespace optical communication," *IEEE Trans. Wirel. Commun.*, vol. 7, no. 12, pp. 5441–5449, Dec. 2008, doi: 10.1109/TWC.2008.071352.

[5] J. Armstrong, "OFDM for Optical Communications," *Journal of Lightwave Technology*, vol. 27, no. 3, pp. 189–204, Feb. 2009, doi: 10.1109/JLT.2008.2010061.

[6] A. M. Khalid, G. Cossu, R. Corsini, P. Choudhury, and E. Ciaramella, "1-Gb/s transmission over a phosphorescent white LED by using rate-adaptive discrete multitone modulation," *IEEE Photonics J.*, vol. 4, no. 5, pp. 1465–1473, 2012, doi: 10.1109/JPHOT.2012.2210397.

[7] J. Grubor, S. Randel, K. D. Langer, and J. W. Walewski, "Broadband information broadcasting using LED-based interior lighting," *Journal of Lightwave Technology*, vol. 26, no. 24, pp. 3883–3892, 2008, doi: 10.1109/JLT.2008.928525.

[8] J. Armstrong and B. J. C. Schmidt, "Comparison of asymmetrically clipped optical OFDM and DC-biased optical OFDM in AWGN," *IEEE Communications Letters*, vol. 12, no. 5, pp. 343–345, May 2008, doi: 10.1109/LCOMM.2008.080193.

[9] A. A. Abdulkafi, M. Y. Alias, and Y. S. Hussein, "Performance analysis of DCOOFDM in VLC system," *2015 IEEE 12th Malaysia International Conference on Communications, MICC 2015*, pp. 163–168, Oct. 2016, doi: 10.1109/MICC.2015.7725427.

[10] F. Miramirkhani and M. Uysal, "Channel Modeling and Characterization for Visible Light Communications," *IEEE Photonics J.*, vol. 7, no. 6, Dec. 2015, doi: 10.1109/JPHOT.2015.2504238.

[11] K. Lee, H. Park, J. R. Barry, and S. Member, "IEEE COMMUNICATIONS LETTERS, ACCEPTED FOR PUBLICATION 1 Indoor Channel Characteristics for Visible Light Communications", doi: 10.1109/LCOMM.2011.010411.101945.

[12] D. Tsonev, S. Sinanovic, and H. Haas, "Complete modeling of nonlinear distortion in OFDM-based optical wireless communication," *Journal of Lightwave Technology*, vol. 31, no. 18, pp. 3064–3076, 2013, doi: 10.1109/JLT.2013.2278675.

[13] M. A. Elkarim, M. A. Elkarim, M. H. Aly, H. M. AbdelKader, M. M. Elsherbini, and M. M. Elsherbini, "LED nonlinearity mitigation in LACO-OFDM optical communications based on adaptive pre distortion and post distortion techniques," *Applied Optics, Vol. 60, Issue 24, pp. 7279-7289*, vol. 60, no. 24, pp. 7279– 7289, Aug. 2021, doi: 10.1364/ao.432364.

[14] M. A. Elkarim, M. A. Elkarim, M. M. Elsherbini, M. M. Elsherbini, H. M. Abdel Kader, and M. H. Aly, "Exploring the effect of LED nonlinearity on the performance of layered ACO-OFDM," *Applied Optics, Vol. 59, Issue 24, pp. 73437351*, vol. 59, no. 24, pp. 7343–7351, Aug. 2020, doi: 10.1364/ao.397559.

[15] H. Yang, T. Wu, and L.-K. Chen, "On the Performance of Adaptive MIMO-OFDM Indoor Visible Light Communications," *IEEE PHOTONICS TECHNOLOGY LETTERS*, vol. 28, no. 8, 2016, doi: 10.1109/LPT.2016.2517192.

[16] Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of Machine Learning in Wireless Networks: Key Techniques and Open Issues," *IEEE Communications Surveys and Tutorials*, vol. 21, no. 4, pp. 302–3108, Oct. 2019, doi: 10.1109/COMST.2019.2924243.

[17] J. Mata *et al.*, "Artificial intelligence (AI) methods in optical networks: A comprehensive survey," *Optical Switching and Networking*, vol. 28, pp. 43–57, Apr. 2018, doi: 10.1016/j.osn.2017.12.006.

[18] W. M. Salama, M. H. Aly, and E. S. Amer, "Deep learning-based channel estimation optimization in VLC systems," *Optical and Quantum Electronics 2022 55:1*, vol. 55, no. 1, pp. 79-, Dec. 2022, doi: 10.1007/s11082-02204363-7.

[19] T. Komine and M. Nakagawa, "Fundamental analysis for visible-light communication system using LED lights," *IEEE Transactions on Consumer Electronics*, vol. 50, no. 1, pp. 100–107, Feb. 2004, doi: 10.1109/TCE.2004.1277847.

[20] T. Wang, F. Yang, F. Yang, J. Song, and J. Song, "Deep learning-based detection scheme for visible light communication with generalized spatial modulation," *Optics Express, Vol. 28, Issue 20, pp. 28906-28915*, vol. 28, no. 20, pp. 28906–28915, Sep. 2020, doi: 10.1364/oe.404463.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

[21] "Fixed Radio Systems; Multipoint Equipment and Antennas; Part 1: Overview and Requirements for Digital Multipoint Radio Systems," 2007.

[22] "1-Gb/s Transmission Over a Phosphorescent White LED by Using Rate-Adaptive Discrete Multitone Modulation | IEEE Journals & Magazine | IEEE Xplore." Accessed: Mar. 06, 2026. [Online]. Available: https://ieeexplore.ieee.org/document/6249713.

[23] J. Vucic, C. Kottke, S. Nerreter, K. D. Langer, and J. W. Walewski, "513 Mbit/s visible light communications link based on DMT modulation of a white LED," *Journal of Light wave Technology*, vol. 28, no. 24, pp. 3512–3518, 2010, doi: 10.1109/JLT.2010.2089602.

[24] X. Li, R. Zhang, and L. Hanzo, "Cooperative load balancing in hybrid visible light communications and WiFi," *IEEE Transactions on Communications*, vol. 63, no. 4, pp. 1319–1329, Apr. 2015, doi: 10.1109/TCOMM.2015.2409172.

[25] H. Alrakah, M. Hijazi, S. Sinanovic, and W. Popoola, "Clipping noise in visible light communication systems with OFDM and PAPR reduction," *Photonics*, vol. 11, no. 7, p. 643, Jul. 2024, doi: 10.3390/photonics11070643.

[26] Z. Yu *et al.*, "Resource-efficient channel estimation for DCO-OFDM based VLC systems," *Optics Express, Vol. 31, Issue 17, pp. 27345-27364*, vol. 31, no. 17, pp. 27345–27364, Aug. 2023, doi: 10.1364/oe.494497.

[27] H. Elgala, R. Mesleh, and H. Haas, "Indoor optical wireless communication: Potential and state-of-the-art," *IEEE Communications Magazine*, vol. 49, no. 9, pp. 56–62, Sep. 2011, doi: 10.1109/MCOM.2011.6011734.

[28] E. B. Bektas and E. Panayirci, "Channel Estimation for DCO-OFDM Based VLC Systems in the Presence of Clipping Noise," *2020 28th Signal Processing and Communications Applications Conference, SIU 2020 - Proceedings*, Oct. 2020, doi: 10.1109/SIU49456.2020.9302481.

[29] F. Mogyorósi *et al.*, "Positioning in 5G and 6G Networks—A Survey," *Sensors 2022, Vol. 22,* vol. 22, no. 13, Jun. 2022, doi: 10.3390/s22134757.

ABOUT THE AUTHOR

Sanghmitra earned her Bachelor's degree in Communication Engineering from Shri Ramswaroop Memorial Group of Professional Colleges in 2017 and is currently advancing her expertise through an M.Tech at the Rameshwaram Institute of Technology & Management in Lucknow. Her primary research focuses on the integration of gyroscopic sensors within Android-based mobile applications, a study that was featured in the *International Journal of Innovative Research in Computer Science and Technology (IJIRCST)* in November 2022.
This academic foundation has allowed her to bridge the gap between hardware sensor data and functional mobile software development.
Beyond her core research, she has established a strong portfolio in "Smart Agriculture" and environmental monitoring. In January 2020, she published a study in the *International Journal of Computer Science and Mobile Applications* regarding a B2C Farming Information System for the fruit crop supply chain in Uttar Pradesh. Her recent collaborative work includes a 2023 paper in *IJSRCEIT* on the statistical quantification of air quality systems and a 2025 publication in *IJIRCST* detailing an IoT-centric platform for real-time CO and methane detection. These contributions underscore her commitment to utilizing geospatial analysis and real-time data to solve modern agricultural and environmental challenges.

Aashu Kori is an Electronics and Communication Engineering professional with academic and technical experience in electronic systems, communication technologies, and engineering education. He holds a Master of Engineering from DAVV University, Indore, and a Bachelor of Engineering from RGPV Bhopal. With a strong foundation in analog and digital circuit design, VLSI concepts, and basic electrical engineering, he has developed both theoretical knowledge and practical understanding of communication systems and network technologies.
Currently serving as an Assistant Professor in the Department of Electronics and Communication Engineering at RITM, Lucknow, Aashu is dedicated to teaching, mentoring students, and contributing to technical education. He previously worked as an Assistant Professor at AITRC, Chhindwara, where he gained valuable academic and research experience. His professional training at Bharat Sanchar Nigam Limited (BSNL), Indore focused on digital communication in computer networks, strengthening his industry exposure. His major project on the reliability evaluation of fiber-wireless access networks explored critical aspects such as survivability, energy efficiency, and optical network unit placement.