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A Review of Indoor Li-Fi Receiver Challenges: Mathematical Models and Testing Approaches

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Abstract. *This work presents a general and introductory review of Visible light communication (VLC) systems represent an effective alternative to conventional wireless communications, providing a fast means of transmitting data in indoor environments. However, the dynamic nature of wireless optical channels poses several constraints that must be taken into account during design, especially at the receiver side. Among the most prominent of these challenges are those related to receiver movement and orientation, which may cause issues related to channel gain and signal to noise ratio (SNR).Since the channel changes continuously over time due to several reasons, including user movement and environmental factors such as dimming during use, accompanied by interference from other ambient lights, researchers are seeking to find accurate and continuous methods for estimation. In addition to the problems that come with relying on line-of-sight (LOS), it imposes limitations and challenges related to signal degradation due to unavoidable obstacles, and thus more efficient nonlinear techniques such as non-line-of-sight (NLOS). Advanced models have been proposed to solve receiver problems, including advanced receiver motion models, such as those for user device orientation based on experimental measurements. Device orientation statistics are presented for both sitting and walking activities, and other random path models based on light direction are considered with the importance of taking into account receiver orientation and motion patterns to improve performance. Also, deep learning methods are effective in improving resource allocation and signal detection to enhance flexibility especially in complex indoor environments. In this paper, the latest developments related to the problems and innovative solutions to ensure reliable communication in visible light communication* (VLC) *networks are discussed.*

Keywords: *Receiver orientation;* signal to noise ratio (SNR)*; Visible Light Communication (VLC); line-of-sight (LOS); non-line-of-sight (NLOS); Deep learning.*

1. INTRODUCTION

An ever-increasing number of users are accessing wireless mobile networks, which has led to a significant increase in the demand for bandwidth due to the spread of fifth-generation networks and advanced wireless applications such as virtual reality (VR), augmented reality (AR), and video streaming [١]. Light-Fidelity (Li-Fi) technology is a new wireless networking technology that uses visible light as a propagation medium [٢]. It is also a VLC-based technology using a broad and unlicensed spectrum of visible light, as an innovative solution to overcome these limitations [3]. Li-Fi cells are smaller than radio frequency (RF) femto cells, and are suitable for deploying ultra-dense cellular networks using light-emitting diode (LED) lamps in indoor environments. Each LED lamp, in addition to lighting, also becomes a wireless access point (AP) and serves multiple user devices (UE) in the associated photovoltaic cell [4].

On the other hand, the limited penetration of visible light networks, due to their limited coverage range, enhances the security and reliability of this type of technology in various applications. Fig 1 shows a typical use of Li-Fi technology in an indoor environment. This system is based on the use of light sources called light-emitting diodes (LEDs) as a means of light transmission, in addition to photodetectors (PDs) that act as receivers, taking into account LOS and NLOS light path. This design reflects the possibility of using light as a means of data transmission within indoor environments, enabling high data rates and secure communications at the same time [5].

Fig 1: Overview of Indoor Li-Fi Communication System

In [6], Li-Fi is a suitable option in a wide range of applications that require high speeds, especially in locations with indoor conditions that limit data traffic. Indoor Li-Fi systems, as highlighted by [7], rely on visible light sources such as LEDs to provide illumination while also transmitting data. A crucial aspect of Li-Fi communication, as [٨] describes, is whether the signal is transmitted via (LOS) or (NLOS) paths. LOS, according to [٩], provides a direct conduit for light signals, which often results in faster data speeds and more consistent connection. However, as [١٠] notes, NLOS transmission, in which light signals are reflected off surfaces, can increase coverage , but it frequently comes at the tradeoff of lower data rates and signal quality.

This paper reviews the current state of Li-Fi technology with a focus on VLC, discussing its technical advancements, key challenges, and potential solutions for optimizing both LOS and NLOS communication scenarios [11]. Specifically, as outlined by [12], this study examines some of the critical technologies and methods that enhance the performance and efficiency of Li-Fi receivers, highlighting the challenges that remain in real-world implementations. Additionally, as [13] indicates, insights are provided into future research directions aimed at improving Li-Fi communication systems for high-demand indoor environments.

The contributions of this study are as follows: (I) a comprehensive literature review on Li-Fi receiver issues, focusing on mathematical models and testing approaches. (II) An analysis of the key architectural features of Li-Fi receivers, highlighting their strengths and limitations. (III) A discussion on the most critical challenges in optimizing Li-Fi receivers, including multi-user access and open research problems.

.The paper is divided into six sections. Section 2 disputes Visible Light Communication (VLC) technology and describes the evaluation process. Section 3 discusses the architecture of Li-Fi receivers and essential technologies. Section 4 investigates the advantages and disadvantages of present receiver designs. Section 5 describes the data gathering methods used to assess Li-Fi system performance, with a focus on signal quality, mobility, and environmental interference. Section 6 wraps up the study by summarizing major findings and suggesting future research directions.

In Table 1, studies on several characteristics of Li-Fi technology are summarized, including some of the advantages, disadvantages, and application areas of such technologies. These studies highlight the limitations of conventional radio communication systems and compare them with LiFi technology, taking into account the requirements related to bandwidth, information security, and light paths (LOS and NLOS) and their impact on performance in indoor environments. hey also highlight the methodologies used in Li-Fi studies, ranging from traditional mathematical models through Lambertian computations to advanced AI techniques and models, such as the use of artificial neural networks (ANNs) and long short-term memory (LSTM) models [6]-[8]. In [9],[10] more accurate methods based on experimental setups and practical data were used to provide a higher level of reliability, especially with regard to challenges related to dynamic issues such as receiver movement and continuous channel changes over time. They also included proposed techniques related to positioning using deep learning, such as artificial neural networks (ANN) and long-short-term memory (LSTM) models, which contributed to improving the accuracy and stability of the system in dynamic environments.

In [6],[9],[10] and [12],One of the main advantages of applying machine learning techniques is their ability to effectively predict and adapt to environmental and user behavioral variables. However, the heavy reliance on simulation-based datasets in many studies suggests the need for more practical testing in real-world environments, in order to bridge the gap between the proposed theories and their practical applicability.

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Table 1: Research Studies with Focus on Methods, Strengths, and Weaknesses

No.	Ref	Key Focus	Methods Used	Strengths	Weaknesses	Data Source
1	[٦]	Bandwidth limitations in RF	Mathematical Modeling	Highlights demand for high bandwidth	Limited real-world applicability	Simulated Data
2	[٧]	Advantages of Li-Fi over RF	Analytical Comparison	Emphasizes immunity to RF interference	Does not address integration with RF systems	Literature-based
3	[٨]	Security in signal confinement	Mathematical Models and Simulation	Discusses improved data security	Lacks experimental validation	Simulated Data
4	[٩]	Li-Fi for indoor applications	Experimental Setup	Demonstrates real-world feasibility	Limited to small-scale environments	Collected Data
5	[١٠]	LOS vs. NLOS paths	Lambertian Model, Reflectivity Calculations	Explores LOS/NLOS trade-offs effectively	Reflectivity assumptions may limit accuracy	Generated Data
6	[11]	Mobility impact on signal quality	Random Waypoint Mobility Models	Addresses user movement impact on signal gain	Requires more complex mobility scenarios	Generated Data
7	[12]	Enhancing data throughput	Sectorized Optical Models	Improves data uniformity in multi-user setups	Limited evaluation in dynamic environments	Simulated Data
8	[13]	Future directions in Li-Fi research	Review of Existing Literature	Proposes methods for enhancing indoor systems	Broad focus lacks detailed technical analysis	Literature-based
9	[9]	Deep learning for user positioning	Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN)	Provides accurate 3D positioning results	Relies heavily on simulated scenarios	Simulated Data
10	[10]	Channel aging solutions	Long Short-Term Memory (LSTM) Models	Predicts mobility impacts with high accuracy	Requires large datasets for model training	Collected Data

Moreover, resource management in multi-user scenarios and optimization of high-density indoor installations have been neglected. To solve these shortcomings, future research should emphasize the integration of machine learning models validated with experimental data, which will improve the practicality and flexibility of Li-Fi systems. By highlighting the strengths and weaknesses, this is a way to create a road map for the development of Li-Fi technology to suit future generations.

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2. Visible Light Communication (VLC) Research

VLC harnesses the power of visible light, which is included in the wavelength spectrum of 380 nm to 780 nm, to facilitate smooth data transfer, offering a bandwidth exceeding 320 THz, making it ideal for high-speed data applications[7]. Room lighting systems are often integrated with VLC to provide a mechanism for optical data transfer, and LEDs are the core component of VLC systems, due to their low cost, high energy efficiency, and compatibility with most infrastructures [10]. Due to the high frequency range of LEDs, they are an important and essential tool for data transmission in indoor VLC systems [14].

The divergent pattern property of LEDs makes them a powerful tool in providing wide coverage by dispersing the light they generate over different angles [15]. Therefore, in general, VLC systems are suitable in environments where direct beam steering is not possible. However, the limited modulation range of standard LEDs limits the use of the full spectrum of visible light in communications [16]. To overcome these challenges and increase data transmission rates, research in this area has mainly focused on improving spectral efficiency [17].

In [18], the use of multiple color LEDs is an effective way to increase spectrum efficiency through a method called wavelength division multiplexing (WDM) where a range of wavelengths can be transmitted simultaneously.

In [20], it was demonstrated that there is a method to increase the data transfer rate by changing the intensity modulation scheme of the coloured LEDs using a modulation method called Color-shift keying (CSK), which is detected by photodetectors upon receipt, where the changes in intensity are captured and converted into bit streams [20], [21]. The researchers in [20] demonstrated that coding improvement methods have a role in increasing the spectrum utilization by using CSK. Optical wireless channels may face problems of propagation delay and path multiplicity, as studies have shown that these problems can be solved by using the four-color CSK, which outperforms the traditional three-color CSK in terms of reliability and efficiency [21].

In [14], some limitations may be imposed due to the frequency ranges of conventional LEDs, where developments in LED materials and device architectures have been studied to overcome these limitations. The characteristics of one type, micro-LED, have been shown to be a promising option for high-speed VLC applications. Also, organic light-emitting diodes (OLEDs) are one of the most interesting types due to their low cost and high efficiency, despite their low transmission capacity compared to conventional LEDs. There are also studies seeking to improve the performance of OLEDs for VLC systems, although they still show lower data transmission rates than some conventional types [22].

3 Indoor LiFi System Channel

The performance and signal quality of an indoor system are affected by several elements such as surface reflections, LOS alignment, and the geometric configuration of the transmitter and receiver, which is the optical path through which data is carried from a light source (transmitter) to a photodetector (receiver) [23].

LOS connection and NLOS channel, which is caused by reflections in the surroundings, are the two main parts of the indoor LiFi channel. As shown in Figure 2, the transmitter and receiver are directly connected by the LOS link. NLOS channel, on the other hand, is made up of innumerable reflected pathways, as shown in Figure 2 [24].

Fig 2: LOS and NLOS Propagation Paths in Li-Fi Systems

An indoor LiFi system's overall channel response is shown in the frequency domain as follows:

$$H_{\mathrm{owc}}(f) = H_{\mathrm{NLOS}}(f) + H_{\mathrm{LOS}}(f) \qquad (1.1)$$

$$= \sum_{n=1}^{\infty} H_{\mathrm{NLOS},n}(f) e^{-j2\pi f \tau_n} + H_{\mathrm{LOS}}(f) e^{-j2\pi f \tau_0} \qquad (1.2)$$

The indoor LiFi channel consists of both LOS and NLOS components, with the overall frequency response expressed as the sum of these two components.

Where :The LOS component, $H_{\mathrm{LOS}}(f)$represents the direct path, while $H_{\mathrm{NLOS}}(f)$accounts for multiple reflected paths. Each component has a corresponding delay, τ_0 for LOS and τ_n for the n-th NLOS path, where d and d_n represent the respective distances. These delays introduce phase shifts in the frequency domain, with c being the speed of light, impacting the signal's overall strength and transmission quality.

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3.1 Line-of-Sight (LOS) Communication in Li-Fi Systems

In [8], LOS communication in Li-Fi systems refers to a direct optical link between a transmitter (such as an LED) and a receiver (such as a light detector). This communication mode generally provides better performance in terms of signal strength and data rate, because it reduces interference and attenuation. Line-of-sight configuration is particularly effective for applications that require high-speed, low-latency data transmission, because it eliminates the multipath effects associated with reflection and scattering.

The **mathematical modeling** of the direct current (DC) gain of the LOS optical wireless channel between the AP and the UE can be obtained as [13]:

$$H_{\mathrm{LOS}} = \frac{(m+1)A_{pd}}{2\pi d^2} \quad cos^{\,m}(\varphi)\ g_f\ cos(\psi)\ \ rect(\frac{\psi}{\Psi c}) \qquad (2)$$

Explanation:

- $\boldsymbol{H_{\mathrm{LOS}}}$**:** Denotes the DC gain of the Line-of-Sight (LOS) component.
- $\boldsymbol{m}$: Lambertian order related to the LED emission pattern.
- $\boldsymbol{A_{pd}}$: is the physical area of the photodetector (PD).
- $\boldsymbol{d}$: Distance between the transmitter and receiver.
- $\boldsymbol{\varphi}, \boldsymbol{\psi}$: The incidence angle with respect to the normal vector to the UE surface.
- $\boldsymbol{g_f(\psi)}$: The gain of the optical concentrator.
- $\boldsymbol{rect(\frac{\psi}{\Psi c})}$: Rectangular function representing the field of view of the receiver.

In [8], [14], it was demonstrated that the more light beams are focused on the receiver (directing) by focusing beam steering techniques, the more system performance can be improved in a controlled line-of-sight situation. Significantly higher data rates and lower bit error rates can be achieved in line-of-sight arrangements when the transmitter and receiver are perfectly aligned.

The function $g(\psi)$ the optical concentrator is defined as:

$$g_f(\psi) = \begin{cases} \frac{\zeta^2}{(\sin \boldsymbol{\Psi c})^2} & ,0 \le \psi \le \Psi\_c \\ 0 & ,\text{otherwise} \end{cases} \qquad (3)$$

The optical concentrator gain $g(\psi)$ is a piecewise function that defines how efficiently light is concentrated onto the receiver, depending on the angle of incidence ψ . For angles within the field of view of the receiver $0 \le \psi \le \Psi\_c$, the gain is given by $\frac{\zeta^2}{\sin^2}$, where ζ is the refractive index. Outside the field of view, the gain is zero, meaning no light is received. This ensures that only light within the desired range contributes to the received signal, improving system efficiency.and also the Lambertian order m:

$$m = -\frac{1}{\log_2\left(\cos \Phi_{\frac{1}{2}}\right)} \qquad (4)$$

Which is a parameter that characterizes the directional radiation pattern of the optical source. The value of m is calculated based on the half-power angle $_{\frac{1}{2}}$, and is given by the inverse logarithmic function involving the cosine of this angle. The negative sign indicates that as the angle increases, the Lambertian order decreases.

$$\cos\varphi = \frac{(-d \cdot n_t)}{\|d\|}, \qquad (5)$$

$$\cos\psi = \frac{d \cdot n\prime_{\mathrm{u}}}{\|d\|}, \qquad (6)$$

Where $n_t = [0,0,-1]^T$ and n_t are the normal vectors of the transmitter and receiver planes, respectively, and d is the distance vector from the receiver to the transmitter. The symbols $\cdot$ and $\|\cdot\|$ represent the dot product and the Euclidean norm, respectively. Additionally, $(\cdot)^T$indicates the transpose of a vector or matrix.

3.2 Non-Line-of-Sight (NLOS)Channel Modeling in Indoor LiFi Systems

NLOS component of the indoor optical channel involves multiple reflections between surfaces, modeled as Lambertian radiators. The environment is segmented into surface elements, each reflecting light beams [8]. The frequency domain of the NLOS channel gain, considering infinite reflections, is expressed as:

$$\boldsymbol{H}_{\mathbf{NLOS}}(\boldsymbol{f}) = \boldsymbol{r}^{\boldsymbol{T}}(\boldsymbol{f}) \cdot \boldsymbol{G}_{\boldsymbol{p}} \cdot \left(\boldsymbol{I} - \boldsymbol{H}_{\boldsymbol{e}}(\boldsymbol{f}) \cdot \boldsymbol{G}_{\boldsymbol{p}}\right)^{-\mathbf{1}} \cdot \boldsymbol{t}(\boldsymbol{f}), \qquad (7)$$

Where $t(f)$ the transmitter transfer is vector and $r\,(f)$ is the receiver transfer vector. The matrix $H_e(f)$ escribes the LOS transfer function between all surface elements, and G_p represents the reflectivity matrix of all reflectors. Each element of the transfer vectors is given by:

$$H_{k,\mathrm{TX}}(f) = \frac{(m+1)A_k}{2\pi d^2 k_{,\mathrm{TX}}} \cdot \cos^{\,m} \varphi_{k,\mathrm{TX}} \cdot \cos\psi_{k,\mathrm{TX}} \cdot e^{-j2\pi f \cdot \frac{d_{k,\mathrm{TX}}}{c}}, \; k = 1, \ldots, \mathrm{N}, \qquad (8)$$

This equation incorporates the areas of the reflectors (A_k) , angles of incidence and reflection $\left(\varphi_{k,\mathrm{TX}}, \psi_{k,\mathrm{TX}}\right)$, and distances between transmitters and reflectors $(d_{k,\mathrm{TX}})$.

4. Challenges in Li-Fi Receiver

In Li-Fi systems, due to the dynamic nature of the optical wireless channel in the internal system, which poses challenges related to the design of efficient optical receivers. Another challenge is that channel gain and SNR are affected by receiver motion and orientation.

In [25], user movement and ambient light interference are taken into account, so it is assumed that most real-world applications, such as mobile phone users who regularly change the position of their devices, are unreasonable to assume that the receiver remains in a stable vertical orientation.. In [25], [26], movement in a Li-Fi system affects the LOS channel gain, which is critical to maintaining a robust connection. For example, user mobility models show that irregular spatial distribution of receivers and variations in device orientation can lead to significant signal degradation. In [25], to provide reliable connectivity, especially in environments with significant user movement, a stable and accurate channel estimation is required. Movement, orientation, occlusion, and interference are major factors that significantly affect the performance of a Li-Fi receiver, posing significant challenges to achieving fault-free connectivity. Reliance on line-of-sight connectivity is a major problem, as variations in incidence angle and field of view (FoV) mean that irregular movements and changes in user equipment (UE) orientation can cause degradation in channel gain, which in turn leads to higher error rates and intermittent links. Fig 3 illustrates the effects on channel gain and signal strength, as a result of changing receiver orientation, demonstrating the importance of maintaining optimal alignment between the LED transmitter and the photodetector to ensure stable and reliable communication.

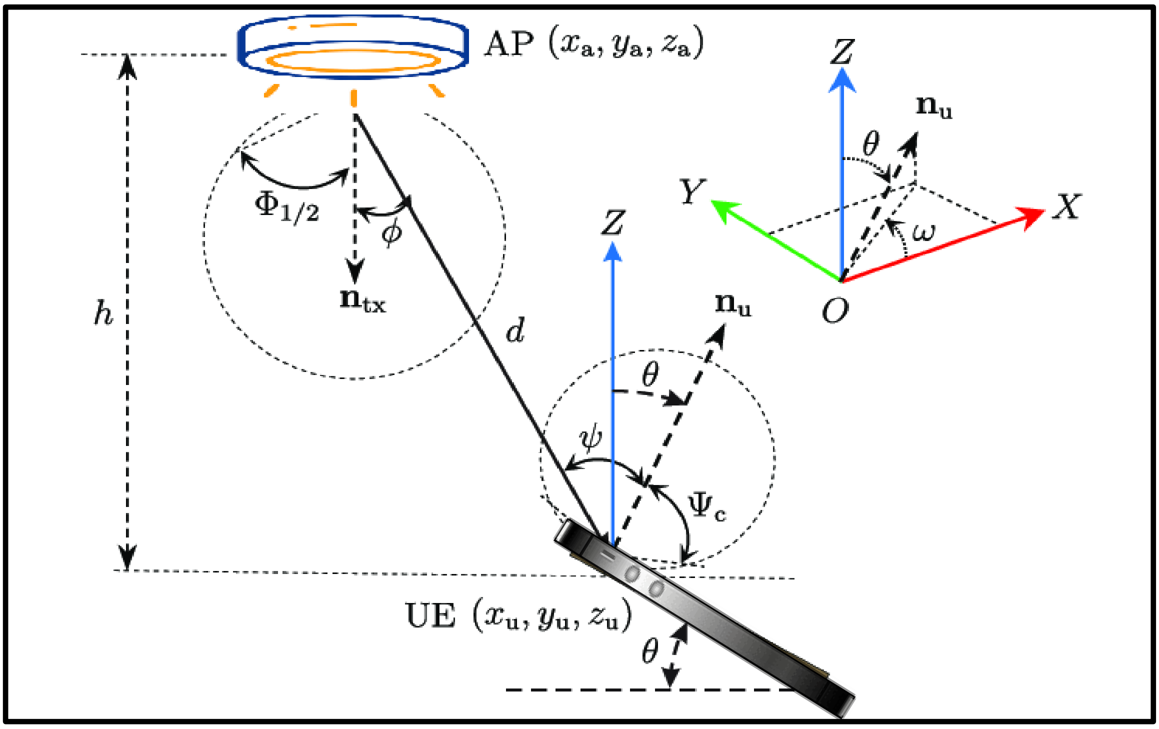

Fig 3: Optical Channel Gain and LED Projection on Side Detectors.

Orientation is another critical challenge, especially as mobile users frequently change the orientation of their devices. The authors explores how such random device orientations affect visible light communication (VLC) performance. Random orientations can lead to misalignments between the light-emitting diode (LED) and the PD, degrading performance, such as reducing SNRs and increasing bit-error rates (BERs) [3]. Similarly, that unpredictable effect of receiver orientation and position variations make it difficult to maintain high communication rates, significantly affecting channel quality in multi-cell indoor VLC systems [25].

Furthermore, Li-Fi systems' resource allocation and signal recognition have a difficult time adjusting to the changing indoor environment. According to the paper Learning Indoor Environment for Effective LiFi Communications, deep learning methods have the potential to alleviate these problems by forecasting indoor environment features like obstruction and user mobility. Particularly when depending on partial channel

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state information (CSI), these approaches outperform more conventional channel estimation methods such as least squares (LS) or minimal mean square error (MMSE) [12].

Finally, issues with cell handover procedures in multi-LED configurations are brought about by user mobility. Receivers have to adjust to different access point (AP) locations and neighboring AP interference, which can be difficult in situations with a high population density.

In [26], [27] it was shown that when users switch locations within different access point coverages with different illumination, it has a significant impact on the quality of service. Here lies the importance and effectiveness of efficient handover techniques necessary to prevent throughput degradation and maintain stable connectivity. Furthermore, as mentioned in [28], robust strategies are needed to solve the problem of environment complexity and unpredictable movement of users for the purpose of resource allocation. Therefore, in [29] have proposed models in advanced machine learning methods, to ensure reliable data transfer rates, reduce delivery rates, and improve resource allocation, even in complex indoor scenarios with high user mobility and dynamic environments.

4. Mathematical Models for Li-Fi Receivers

Providing theoretical basis through mathematical models is of great importance, as it is important to analyze the interactions between transmitted light signals and receiving mechanisms, thus improving the performance of Li-Fi receiver. Among the models related to determining the metrics are SNR, autocorrelation function, channel distortion, channel coherence time, and the influence of external factors on signal propagation [30].

4.1 The Modified Truncated Laplace (MTL) Model

The PD has an impact on the LOS channel gain, so the elevation angle distribution in fixed Li-Fi receivers is typically represented by the MTL model, which is approximated using the truncated Laplace distribution [6].

The probability density function (PDF) of the truncated Laplace distribution for the elevation angle θ is expressed as:

$$f(\theta) = \frac{\sqrt{2}}{\sigma_\theta} \cdot exp\left(-\frac{|\theta-\mu_\theta|\sqrt{2}}{\sigma_\theta}\right) \ ,0 \le \theta \le \frac{\pi}{2} \qquad (9)$$

Where the elevation angle's mean and standard deviation are represented by μ_θ and σ_θ, respectively. The elevation angle distribution, which yields the LOS channel gain H_{LOS} is described by this equation. The Laplace distribution is appropriate for forecasting stationary users' signal reception since it accurately models their direction.

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4.2 The Modified Beta (MB) Model

For mobile users, because it takes into account both random direction and motion, the Modified Beta (MB) model accurately represents the line-of-sight channel gain. MB represents the line-of-sight channel gain accuracy for mobile users, because it takes into account both random direction and motion. The effect of user mobility on signal reception is estimated using the Beta distribution [6]. The following provides its probability density function (PDF):

$$f(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha,\beta)} \qquad (10)$$

Where α and β are the shape parameters of the distribution, and $B(\alpha,\beta)$ is the Beta function. This distribution models the random nature of the PD orientation as users move within the environment, which in turn influences the LOS channel gain.

The PDFs of MTL, MB, and Gaussian distributions for simulating Li-Fi receiver elevation angles are contrasted in Fig 4. Gaussian (green) is used as a baseline for variability, MB (blue) simulates the wider orientations of mobile users, and MTL (red) represents stationary users. Their impact on channel gain and significance in indoor Li-Fi environments are highlighted by the comparison with sample data.

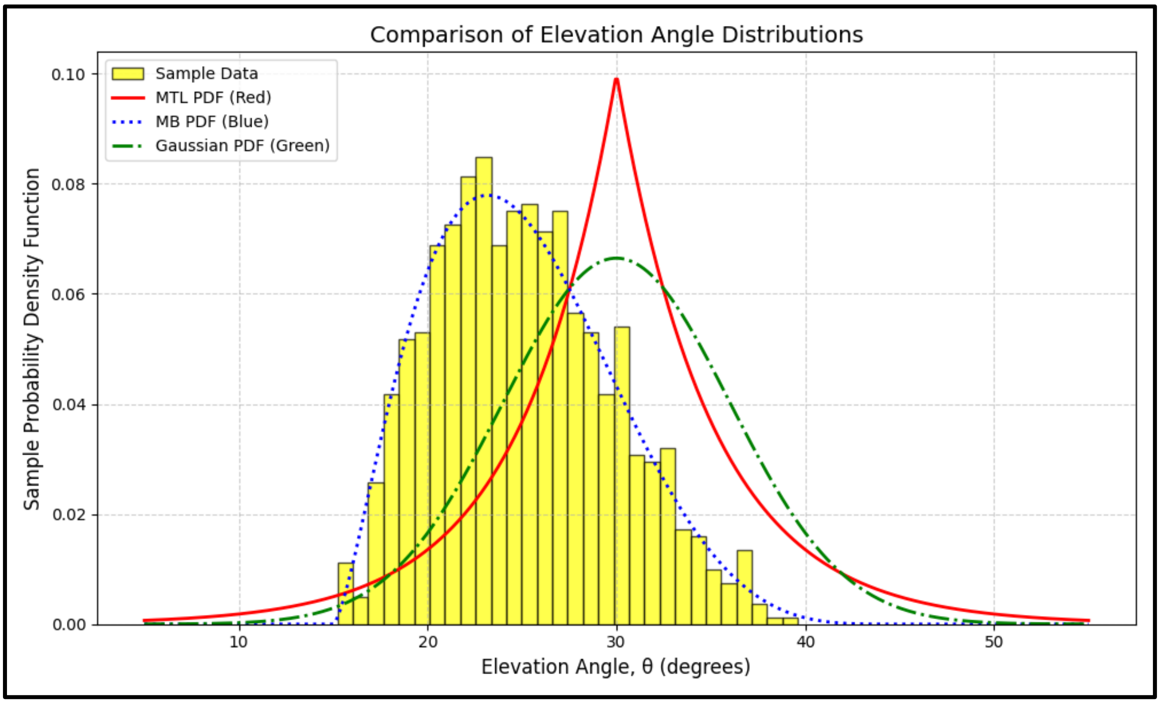

Fig 4: Comparison of the Modified Truncated Laplace (MTL), Modified Beta (MB), and Gaussian Distributions

4.3 The Lambertian Model

In order to explain the gain between the LED and photodetector (PD) in a mobile Li-Fi system [6], [25] applies the Lambertian model to the LOS channel gain. This model indicate the optical propagation between the light source and receiver and is is given by:

$$h_{\mathrm{LOS}} = \frac{(m+1)A_{PD}\, g_f \cos^m\varphi \cos\psi}{2\pi d^2}, \quad 0 \le \psi \le \Psi_{\mathrm{FOV}}\,, \qquad (11.1)$$

$$h_{\mathrm{LOS}} = 0\,, \qquad \psi \ge \Psi_{\mathrm{FOV}} \qquad (11.2)$$

where m is the Lambertian order, A_{PD} is the receiving area of the PD, g_f is the optical concentrator gain, φ and ψ are the emission and incidence angles, respectively, and d is the distance between the LED and PD. This model helps predict how varying PD orientations affect the received signal strength in a mobile setting.

5. Data Generation and Collection

This section highlights one of the most important procedure for gathering, quantifying, and evaluating various kinds of data using a set of accepted, validated methods. The primary goal of data collection is to obtain trustworthy and information-rich data, which will then be analyzed to help make important business decisions and assess how well Li-Fi systems function in mobile environments. Activities involving supervised learning require sufficient amounts of data with well-labeled factual information. However, current research on neural handoff algorithms lacks comprehensive details on the generation of labeled data [37] to the best of our knowledge.

5.1. Signal Quality Measurements

In [14], the authors collect data on SNR and BER during experiments. The collected SNR and BER values are then processed and recorded into a dataset. The benefit of this data collected in different lighting scenarios and with different receiver orientations is that it gives an impression of how well Li-Fi receivers perform. In addition to calculating the signal-to-interference ratio plus noise ratio (SINR) data for individual users on all Li-Fi channels.

5.2. Mobility Data

In [7] and [12], in order to enhance understanding of how user device movement affects Li-Fi communications in an indoor environment, data on receiver movement patterns and orientation speed are collected. Changes in signal strength and connection are correlated with changes in user position using motion sensors and location monitoring.

5.3. Environmental Interference Data

Data on indoor environments such as ambient light levels and the presence of physical obstacles are collected to measure the extent to which environmental factors affect Li-Fi receiver system performance, and to measure the extent to which these obstacles affect signal strength and overall system reliability. A comprehensive understanding of the relationship between elements and system performance is provided by analysing the collected data [9].

5.4. Channel Estimation Data

In [11] , channel estimation studies, data is Collected to assess the Li-Fi system's capacity to estimate and adjust to the time-varying characteristics of optical channels. Actually, the accuracy of the channel estimation will be impacted by the position and orientation estimation errors, which will also have an impact on the dependability and achievable rates of LiFi systems.

6. Optimization and Improvement Strategies

To improve performance and adaptability in indoor environments with dynamic contexts, the authors propose several strategies through research on mobile Li-Fi system optimization, including:

6.1. Multi-Photodiode (PD) Configurations

Using multi-PD arrangements is one efficient way to improve mobile Li-Fi performance. To maintain LOS communication with the light source regardless of movement or orientation, this method entails outfitting devices with several photodiodes oriented in various orientations. The basic idea is using multi-PD to calculate the angle while using the received signal strength (RSS) method to calculate the distance. In [32], [38], can use the multi-PD which is configured to receive the data in parallel or add more transmitters. Also, the light reflection from a certain device a concentrator.it was demonstrated that this configuration provides a more robust connection, achieving data transmission rates of up to 36 Mbit/s in mobile environments. Also, other research demonstrates that multi-PD configurations reduce signal loss brought on by device rotation and orientation variations, guaranteeing more dependable and steady connection, as well as the received signal strength indications, [10].

6.2 Channel Estimation Techniques

Channel estimation is one of the main important tasks in realizing practical intelligent reflecting surface-assisted multi-user communication (IRS-MUC) systems. However, unlike traditional communication systems, the IRS-MUC system generally involves a cascaded channel with advanced, statistical distribution. In this case, the optimal minimum mean square error (MMSE) estimator requires multi-dimensional integration calculation, which is complex to perform in practice.Channel estimation is the process of determining the characteristics of a channel. There are several steps in the channel estimation process. The channel is first represented mathematically. After that, a signal that is known to both the sender and the recipient is sent over the channel. For mobile Li-Fi systems to improve communication quality. The study presents two cutting-edge techniques: (1) Channel Estimation Coding, and (2) a Convolutional Deep Residual Networks (CDRN)-based Deep Learning-based Estimation Scheme [32]. By precisely forecasting channel fluctuations based on the spatial properties of the channels, the CDRN approach beats conventional least squares (LS) estimation, improving signal quality and stability. By reducing noise and guaranteeing effective power consumption, the channel estimation coding technique significantly improves communication. The estimated channel state is modelled by the following equation $\hat{h}$:

$$\hat{h} = h + \sum_{n=1}^{L} \omega[\mathrm{n}] z[n] \qquad (17)$$

Where h represents the true channel state, $\hat{h}$ represents the estimated channel state, $\omega[n]$ the pilot signal pattern, and $z[n]$ represents the noise. This general formulation optimizes the pilot signal to minimize noise and improve channel estimation accuracy.

Even while effective, the deep learning method adds a lot of computational complexity, which makes it challenging to use on mobile devices with constrained processing power. Lightweight neural network models that preserve accuracy while being more computationally efficient may be investigated in future studies [33].

6.3. LSTM-Based Channel Tracking

Channel tracking scheme to enhance the communication lifi system performance. In [11,32], One significant contribution is the real-time channel tracking made possible by Long Short-Term Memory (LSTM) networks. due to the time-varying nature of mobile Li-Fi channels, which supports mobile communication, it is critical to estimate accurate channel state information (CSI). In contrast to more conventional techniques like recurrent neural networks (RNNs), the LSTM model performs very well by identifying temporal relationships in channel data and providing more precise predictions of the channel state.

The LSTM tracking process is represented by recursive equations such as:

$$C_n = C_{n-1} \cdot f_n + \tilde{C}_n \cdot i_n \qquad (18)$$

Where C_n is the cell stateand , $C_{n-1}$is the cell state from the previous time step, f_nThe forget gate value , $\tilde{C}_n$ the candidate cell state and , i_n The input gate value .

6.4. Multiple-Input Multiple-Output (MIMO) configurations

In [13], MIMO technology is used to significantly improve system performance and data rates by using different materials and techniques on LEDs and PD. This setup enables the simultaneous transmission and reception of parallel data streams, increasing the overall data throughput and reliability of the Li-Fi system. MIMO is very useful in situations with high mobility or complicated channel conditions because it uses spatial diversity to improve signal quality, reduce interference, and maximize available capacity.. The data rate in a MIMO scenario is expressed as:

$$R_4 = -\frac{B}{ln2} - 2B \sum_{k=1}^{M} p_k E_z \{\log_2 \sum_{k=1}^{M} p_m \times \exp\left(-\frac{(q^T H\omega(s_k - s_m) + \sqrt{B}z)^2}{2B\sigma^2}\right). \qquad (19)$$

Where p_k and p_m represent the probabilities of states k and p_m, q^T is the transposed beamforming vector, H is the channel matrix, ω is the weighting factor, and $s_k - s_m$ denotes the difference between signal states. The term $\sqrt{B}z$ accounts for noise, while σ^2 represents noise variance.

6.5. Coherence Time Optimization

For mobile LiFi systems to sustain reliable connection in dynamic situations, coherence time must be understood and optimized. in [32], Coherence time in mobile LiFi settings is thoroughly examined which also offers mathematical models and experimental support to tackle the difficulties caused by quickly

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changing channels. Coherence time is the amount of time before notable changes brought on by user movement or other environmental events, during which the channel conditions stay largely constant. coherence time models as follows:

$$Tc = n_c \Delta t, \qquad (12)$$

Where Tc is the coherence time it important for the LiFi channel remains stable, n_c is the number of samples for which the channel's autocorrelation function remains above a predefined threshold, and Δt is the time interval between samples.

In [11], the authors proposed to maximize system performance, based on coherence times in common mobile Li-Fi applications are on the scale of tens of milliseconds. The system can predict changes in channel conditions and adjust appropriately by having a thorough understanding of coherence time.

7. Evaluation Criteria

The LiFi technologies are in front of different kinds of performance issues in the terms of channel stability, error performance, and noise resilience in dynamic situations is offered by these metrics: coherence time, BER, and SNR. When combined, they make it easier to optimize communication quality and system reliability, guaranteeing effective operation under a variety of mobile and changing circumstances.

7.1 Coherence Time and Autocorrelation Analysis

In [30], the authors discuss the channel coherence time, It measures the channel's stability over time as users shift. As can be seen below, the coherence time is calculated using the channel gain's autocorrelation function:

$$n_c = \arg_k \left(\rho_L(k) = \eta_{\text{th}}\right) \qquad (13)$$

Where $\rho_L(k)$ is the normalized autocorrelation coefficient, η_{th} is the threshold autocorrelation coefficient, and $\arg_k$ The argument k where $\rho_L(k)$ first equals η_{th}. This formula is crucial for calculating how mobility affects Li-Fi channel variability in real-time situations.

In addition, the autocorrelation function of the channel gain $h[n]$ is presented as:

$$C_h[n] = E[(h[n] - h^{-})(h[n+L] - h^{-})] \qquad (14)$$

Where L the time is shift, and h^{-} is the mean channel gain.

7.2 Error Performance and Optimization

In [31], [39], the authors analyze the device orientation and assess its importance on system performance. Through the PDF of the SNR, BER of DC-biased optical orthogonal frequency division multiplexing (DCO-OFDM) in additive white Gaussian noise (AWGN) channels is evaluated. A careful examination of various performance issues in Li-Fi technology was conducted and finally a solution was proposed to improve its performance. This was done through an experimental approach of the proposed VLC model that recognizes physical layer models that depict the observed range drawn for a variety of optical modulation schemes. the BER can be written as follows:

$$\mathrm{BER} = Q\left(\sqrt{\frac{2SNR}{N_0}}\right) \qquad (15)$$

Where N_0 is the noise power spectral density, and SNR is the signal to noise ratio. The function $Q(\mathrm{x}\,)$) is the Q-function, which is the tail probability of the standard normal distribution, which provides the likelihood of bit errors.

7.3 The signal-to-noise ratio (SNR) model

One notable challenge with LiFi data is the low signal-to-noise ratio (SNR) posing difficulty when applying deep learning techniques especially in dynamic settings with wide variations in noise and interference. Signal quality is measured by the SNR, which quantifies the ratio of the desired signal strength to the background noise and interference power. It has a direct impact on the system's capacity to sustain dependable communication because higher SNR is generally associated with lower BER and more effective data transfer. In mobile Li-Fi systems, elements like ambient light interference, device orientation, and mobility patterns can significantly impact the SNR [3].

In the indoor VLC communication system, the signal-to-noise ratio at the receiving end is expressed as follows [3]:

$$\gamma = \frac{P_r}{N_0 \mathrm{B}} \qquad (16)$$

Where P_r is the received power, N_0 is the noise power spectral density, and B is the channel bandwidth. This equation is fundamental for assessing the receiver's ability to maintain high-quality communication under different noise and environmental conditions.

Table 2 summarizes the main models designed to address challenges in Li-Fi and OWC systems generally, specifically focusing on mobility, orientation, and environmental interference. The Multi-LED Handover Model [26] optimizes handover processes in multi-cell configurations, ensuring uninterrupted connectivity during user movement. The Modified Truncated Laplace Model is incorporated into the Orientation-Based Channel Model ([10]) to precisely describe how device orientation affects signal reception, enhancing the dependability and functionality of Li-Fi systems under different user orientations.

In [8] and [10], The authors proposed an extended orientation-based random waypoint motion model, in which the random orientation of the user device during both walking and stopping time is considered. The model parameters are set based on experimental measurements of the device orientation. Meanwhile, in [4], the Deep Learning Signal Detection Model leverages CNN and RNN to enhance real-time channel estimation in dynamic environments. Additionally, in [5], the Orientation-Based Random Waypoint Model (ORWP) integrates orientation and field of view calculations to assess channel quality in Multi-cell environments.

In [11] and [12], the Joint Position-Orientation Deep Learning Model utilizes deep learning for simultaneous position and orientation estimation, Enhancing signal reliability. In [25], the Angle Effect Model employs the Lambertian Reflection Model to evaluate the effects of receiver orientation on channel gain. Furthermore, in [11], by using LSTM to anticipate and adjust to channel aging, the Proactive Channel Aging Model increases system reliability in dynamic settings.

Table 2. Specific Models and Analytical Method in Indoor Li-Fi System Studies

No.	Ref	Model Name	Analytical Method	Description
1	[26]	Multi-LED Handover Model	Handover Rate Equations	Analyses handover dynamics in multi-cell Li-Fi setups to maintain connectivity.
2	[10]	Orientation-Based Channel Model	The Modified Truncated Laplace (MTL) Model	Uses truncated Laplace distribution to account for device orientation's effect on signal reception.
3	[8],[10]	Random Waypoint Mobility Model	The Modified Beta (MB) Model	Simulates random user movement and orientation, focusing on signal strength variations.
4	[4]	Deep Learning Signal Detection Model	Deep Neural Networks (CNN, RNN)	Applies deep learning to detect environmental changes, improving channel estimation accuracy.
5	[5]	Orientation-Based Random Waypoint Model (ORWP)	Orientation and Field of View (FoV) Calculations	Models mobility and orientation to assess channel quality in dynamic multi-cell Li-Fi setups.
6	[11],[12]	Joint Position-Orientation Deep Learning Model	Deep Learning (Joint Regression and Classification)	Enhances signal stability by estimating both user position and orientation simultaneously.
7	[25]	Orientation Impact Model	The Lambertian Model	Analyzes how random receiver orientations influence channel gain using Lambertian radiation patterns.
8	[11]	Proactive Channel Aging Model	Long Short-Term Memory (LSTM)	Predicts the impact of channel aging on data rates, enabling proactive adjustments in real-time.

8. Future Directions in Li-Fi Receiver Development

The advancement of efficient and reliable Li-Fi receivers still ongoing an active area of research, with several interesting directions identified for future exploration [34]-[36].The need for high-speed indoor wireless communication is growing due to user mobility and rising data rates, which makes developing reliable Li-Fi systems increasingly difficult. The following are some important avenues for future Li-Fi receiver development:

8.1 Adaptive Receiver Design

One of the key difficulties in Li-Fi systems is maintaining reliable interaction in dynamic environments. With the unpredictable behaviour of device orientation and user mobility, adaptive receiver designs are essential. These designs must be able to modify settings in real-time to improve transmission efficiency, even when the photodetector (PD) is not aligned with the light source. This includes the development of multi-directional receivers that can capture signals from multiple angles without the need for mechanical adjustments. Such receivers have already demonstrated improvements in SNR and BER performance under random orientation conditions [14].

8.2 Machine Learning for Channel Estimation

In [14], the authors highlight one of the Main challenges in Li-Fi systems: ensuring Stable communication in Dynamic environments. With the Random nature of device orientation and user movement, they emphasize the importance of Adaptive receiver designs. These designs adapt their configurations instantaneously to Optimize signal reception, even when the PD is misaligned with the light source. The study further explores omni-directional receivers capable of detecting signals from multiple angles without requiring manual adjustments. Such designs have shown notable enhancements in SNR and BER performance under arbitrary orientation scenarios.

8.3 Integration with RF Systems

In [10]-[13], the authors discuss the potential benefits of integrating it with current RF systems, presenting a hybrid approach for continuous connectivity. This combined approach utilizes the advantages of both Li-Fi and RF technologies, such as employing RF for NLOS communication and Li-Fi for High-data transmission in direct line communication. The hybrid system is especially advantageous in environments where Li-Fi coverage may be obstructed by physical barriers or when users move outside the coverage area of a Li-Fi attocell.

8.4 Energy Efficiency and Green Communication

In [13], One of the main concerns for upcoming wireless communication systems, especially Li-Fi technologies, is energy efficiency. For sustainable deployment, it is essential to optimize the power consumption of both transmitters (LEDs) and receivers (PDs). The goal of research should be to lower Li-Fi receiver power needs without compromising functionality. The creation of energy-harvesting receivers that can be powered by the communication signal itself or ambient light is one viable approach.

8.5 Multiple-input multiple-output (MIMO) for Li-Fi

In this subsection, highlight a LiFi MIMO channel is considered, where Nt light sources (e.g. one or multi LEDs) can transmit the signal and one UE receives the signal with N_r PDs. The resulting channel is described as:

$$y = Hx + n \qquad (17)$$

In [13], simple adaptive method is proposed for MIMO VLC to increase the energy efficiency. Li-Fi is also seeing an increase in the utilization of MIMO systems, which are frequently employed in RF communications. Multi LEDs transmitters can connect with Multi PDs receivers thanks to MIMO technology in Li-Fi, which can increase data flow and improve reliability. According to the proposed adaptive method was that chooses the minimum energy-consuming MIMO technique in different positions of the room for a desired reliability ,spectral efficiency and a target BER.

9. CONCLUSIONS

This paper discusses the Key issues and progress in the field of indoor optical wireless communication (OWC) systems, with a particular focus on improving receiver architecture and optimizing system performance. discusses a model for device orientation based on the experimental measurements is proposedThe varying characteristics of optical wireless channels, influenced by factors such as mobility, orientation, and environmental interference, remains a primary obstacle in achieving reliable communication. To address these challenges, mathematical or Analytical models like MTL and MB distributions have proven effective in analyzing user behavior and channel gain. Furthermore, shown that the PDF of the polar angle follows a Laplace distribution for static users while it is better fitted to a Gaussian distribution for mobile users..In addition, the effect of random orientation and spatial distribution of LiFi users on the error performance of LiFi users was investigated based on the derived models. Hybrid approaches, such as combining Li-Fi with RF systems, could provide seamless connectivity in environments with mixed communication needs. In order to maximize performance in practical applications, future research should prioritize energy-efficient solutions and lightweight machine learning methods. Li-Fi technology, which provides fast, secure, and dependable access, has the potential to completely transform indoor wireless communication with further development.

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