Jurnal ELTIKOM :
Jurnal Teknik Elektro, Teknologi Informasi dan Komputer

Vol. 10, No. 1, June 2026, page. 1-10
ISSN 2598-3245 (Print), ISSN 2598-3288 (Online)
DOI: http://doi.org/10.31961/eltikom.v10i1.1652
Available online at http://eltikom.poliban.ac.id

ADAPTIVE POWER MANAGEMENT FOR MULTI-USER INDOOR LIFI COMMUNICATION SYSTEMS USING EVOLUTIONARY ALGORITHMS

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Received: 15 June 2025 – Revised: 3 December 2025 – Accepted: 10 December 2025

ABSTRACT

Visible Light Communication (VLC) systems have emerged as a promising alternative to RF-based solutions, especially in electromagnetic-sensitive environments such as hospitals and aircraft cabins. This study presents a MATLAB-based simulation of an indoor VLC setup using corner and center LED array layouts in an emergency room scenario. The model supports variations in room length and user density and applies a genetic algorithm (GA) for dynamic LED current optimization to improve coverage fairness. This paper proposes an adaptive beam-shaping and power-optimization framework for multi-user indoor LiFi communication systems. The design is particularly suited for environments sensitive to electromagnetic interference (EMI), such as hospitals and emergency rooms, where RF-based systems may pose risks or interfere with medical equipment. Simulation results show that the corner configuration consistently outperformed the center configuration in terms of minimum and average received power, especially in larger rooms (10 m to 12 m) and with higher user numbers (6 to 8). For instance, in the corner case, the mean received power changed from 1.4075×10^{-6} to 1.3808×10^{-6} W when the number of users increased from 6 to 8, whereas in the center case it dropped from 1.0154×10^{-6} to 7.9926×10^{-7} W. Additionally, the optimal minimum power improved in larger rooms and with higher user densities, thus helping maintain communication even for the weakest users. The results confirm that GA-based current shaping improves energy efficiency and signal distribution, making this approach valuable for robust and future-ready VLC applications in emergency scenarios.

Keywords*: beam shaping, emergency room networking, genetic algorithm optimization, LiFi communication, visible light communication (VLC).*

I. INTRODUCTION

IN operating rooms, emergency rooms, and intensive care units, where electromagnetic interference must be avoided, LiFi has emerged as a promising alternative to RF technology [1], [2], [3]. The development of the Internet of Things (IoT) has transformed communication paradigms over the past two decades. In its early stages, IoT systems were mainly characterized by basic sensor networks and simple remote monitoring applications that relied heavily on low-power, low-data-rate communication technologies such as ZigBee and RFID [4], [5]. As demand grew for more intelligent environments, higher performance in latency, reliability, and scalability became necessary. With the integration of cloud computing and edge computing with IoT architectures, more advanced systems with real-time decision-making capabilities and large-scale data aggregation were developed [6], [7]. This shift marked the beginning of more future-ready IoT infrastructures capable of meeting the growing demands of next-generation networks.

Enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communications (mMTC) brought new momentum to IoT infrastructure through 5G

[8], [9]. Researchers recognized that more advanced infrastructure would be needed as emerging applications such as autonomous vehicles, augmented reality (AR), industrial automation, and remote healthcare began to test the limits of 5G. For this reason, 6G cellular networks have become a major focus of current research. These networks are expected to support ultra-high-density connectivity for trillions of devices, terabit-level data rates, and sub-millisecond latency [10], [11]. So far, 6G represents a fundamental shift in IoT service capabilities rather than a simple evolution.

6G-era IoT devices are expected to operate with unprecedented intelligence and autonomy. Semantic communications, AI-native networks, and Integrated Sensing and Communication (ISAC) have emerged as key concepts expected to reshape the context awareness and performance of IoT communications [12], [13]. This shift is driven by highly advanced AI algorithms embedded into communication protocols at the lowest level, enabling predictive resource management, network self-optimization, and context-aware services [14], [15]. As a result, IoT systems are moving from traditional passive data collection frameworks toward proactive, cognitive agents within cyber-physical systems. In addition, new physical-layer technologies are being explored to meet the demands for higher data throughput and greater transmission reliability in next-generation IoT systems. Optical wireless communication, particularly Light Fidelity (LiFi), is emerging as a complementary technology to traditional radio frequency (RF)-based systems because of its high bandwidth, inherent security, and immunity to electromagnetic interference [16], [17]. At the same time, Reconfigurable Intelligent Surfaces (RIS) and Terahertz (THz) communications are being studied to improve wireless channel control and enhance data rates, respectively [18], [19]. Together, these technologies have the potential to make IoT systems more reliable and efficient, even under highly challenging propagation conditions.

Ultimately, the convergence of the Internet of Everything (IoE), advanced wireless technologies, and artificial intelligence (AI) is driving the development of highly adaptive and ultra-reliable IoT networks that can support critical 6G applications. To address the extremely dense deployment of IoT devices and the dynamic nature of modern environments, intelligent resource management solutions, such as AI-based beamforming and power control in LiFi and FSO networks, are becoming increasingly important [20], [21]. By proposing an AI-optimized power control system for an indoor LiFi environment and focusing on reliable communication between medical devices and mobile users in a complex emergency room layout, this study contributes to that direction.

This study addresses the challenge of ensuring reliable and consistent signal reception for users under adverse spatial conditions. It develops a simulation-based VLC model capable of optimizing LED current allocation using genetic algorithms (GA) to maximize the minimum and average received power. Its main contribution lies in integrating a GA-based dynamic beam-shaping technique that adapts to spatial variations in user distribution and room geometry while comparing the performance of corner and center LED configurations. The novelty of this work lies in its comprehensive performance evaluation across different spatial conditions and user groups, showing for the first time that corner LED placement, combined with GA optimization, significantly improves signal fairness and energy efficiency for VLC-based emergency communications. To support real-world deployment, especially in EMI-sensitive environments such as emergency rooms, the proposed system offers a controllable and secure alternative to RF-based wireless networks. A genetic algorithm (GA) is integrated into the beam-shaping and power-control mechanism to dynamically optimize LED array output. This approach helps ensure robust coverage for both stationary and mobile users while minimizing transmission power and maintaining safety compliance.

The remainder of this paper is organized as follows. Section II reviews existing studies on AI-based adaptation techniques for LiFi and optical wireless systems. Section III describes the system model, including the mathematical models for indoor layouts, user placement, and LiFi links. Section IV presents the simulation results and highlights the performance of the proposed AI-based power control under various LED layout scenarios. Finally, Section V concludes the paper and suggests directions for future research.

II. Related Works

Recently, there has been growing interest in applying Artificial Intelligence (AI) to wireless communication systems, particularly for optimizing resource allocation in dynamic environments. For power control in ultra-dense networks, the authors in [22] explored reinforcement learning techniques and reported notable improvements in both coverage and energy efficiency. Similarly, [23] proposed a deep learning-based approach for beam management in millimeter-wave networks, demonstrating the potential of data-driven models to manage complex wireless environments where traditional optimization methods are becoming less effective.

In optical wireless communications, researchers have recently shown growing interest in optimizing LiFi and VLC systems through intelligent techniques. For example, [24] proposed an AI-optimized system that dynamically balances loads across multiple LEDs in an indoor LiFi environment to maximize user throughput and fairness. Another important study, [25], employed deep reinforcement learning for access point selection and handover in hybrid RF/VLC networks, highlighting the value of AI in maintaining seamless connectivity in heterogeneous systems.

Recent research has also examined beamforming and power control in LiFi and Free Space Optical (FSO) communications. In [26], an adaptive beam-steering algorithm was proposed for indoor optical wireless networks, allowing the transmitter to direct the beam dynamically toward mobile users in order to reduce path loss. In contrast, [27] investigated hybrid FSO/RF systems in which machine learning estimators predict atmospheric turbulence conditions so that transmission parameters can be reconfigured to improve reliability under changing weather conditions.

In addition, researchers have begun to examine the deployment and optimization of LiFi networks in specialized environments such as hospitals and emergency departments. In [28], the authors studied the use of LiFi systems for hospital patient monitoring and identified advantages such as electromagnetic immunity and high data rates. Building on this, [29] showed that power control methods, especially when combined with AI algorithms for real-time decision-making, can improve link reliability in LiFi-enabled medical IoT applications. These developments suggest that AI-enhanced optical wireless communication for high-priority, safety-focused indoor applications deserves further attention.

Although previous studies have explored AI-based optimization in VLC systems, most have focused on static coverage maximization, LED placement, or spectral efficiency, while giving limited attention to dynamic settings with mixed user types or real-time beam shaping. Unlike those approaches, our work examines adaptive power control and beam-direction targeting in a setting where mobile and stationary users coexist. Moreover, by emphasizing applicability in EMI-sensitive healthcare settings such as emergency rooms, this study addresses a clear gap in the LiFi deployment literature. To the best of our knowledge, this is the first implementation to combine genetic algorithm-based dynamic tuning with realistic medical usage scenarios, thereby bridging both a practical and a technological research gap.

III. RESEARCH METHOD

The rapid expansion of wireless networks in healthcare environments, especially in emergency rooms, has raised increasing concern about electromagnetic interference (EMI) with sensitive medical equipment. Traditional RF-based systems such as WiFi operate at frequencies that may interfere with critical medical devices such as infusion pumps, ventilators, and patient monitors. In addition, WiFi congestion and security vulnerabilities may affect the reliability of patient data transmission. To address these challenges, Light Fidelity (LiFi) has emerged as a promising solution because it uses the visible light spectrum, which enables high data rates without generating EMI. Lifi systems also provide inherent security through the physical confinement of light within indoor spaces and can operate at gigabit speeds, making them a strong candidate for connectivity-enhancing applications in medical emergency settings. The indoor environment considered in this study models an emergency room with dimensions of Lx = 10 m, Ly = 6 , and Lz = 3. The LED array is mounted either symmetrically or asymmetrically on the ceiling, depending on the layout design being tested. Six stationary users, such as patient monitoring equipment, are randomly placed in the room, while one mobile user, such as a nurse carrying a tablet, follows either a linear or nonlinear path to reflect real-world movement. The user locations and movement paths are designed to test both coverage uniformity and dynamic adaptation requirements.

Each transmitter is modeled as a Lambertian emitter, where the radiation intensity R(θ) at an angle θ from the transmitter normal at (1) [30] where m is the Lambertian emission order, given by (2) and $\emptyset_{1/2}$ is the LED semi-angle at half power. A typical value is $\emptyset_{1/2} = 60°$, which results in $m \approx 1$. The power radiated toward a user is influenced by both the transmitter radiation pattern and the receiver orientation.

$$R(\theta) = \frac{m+1}{2\pi} cos^m(\theta) \qquad (W/sr) \tag{1}$$

$$m = \frac{-\ln(2)}{\ln(\cos(\emptyset_{1/2}))} \tag{2}$$

$$H(o) = \begin{cases} \frac{(m+1)A_{det}}{2\pi d^2} cos^m(\phi)\cos(\psi), & 0 \le \psi \le \psi_c \\ 0, & \psi > \psi_c \end{cases} \tag{3}$$

$$P_r = P_t \times H(0) \tag{4}$$

$$\max_{t_1, t_2, \ldots\ldots\ldots t_N} \left(\min_u P_r(u) \right)$$
Subject to: (5)
$$0 \le P_{t,i} \le P_{max}, \qquad \forall i$$

$$\max_{P_t}(\min_{u \in U} P_r(u))$$
Subject to: (6)
$$0 \le P_{t,i} \le P_{max}, \qquad \forall i = 1,2, \ldots \ldots \ldots N$$

$$F(P_t) = \min_{u \in U}(\sum_{i=1}^{N} P_{t.i} H_{i,u}(0)) \tag{7}$$

The direct current gain *H*(0) of the optical wireless channel is modeled as (3) where A_{det} is the effective detection area of the photodetector, *d* is the distance between the LED and the receiver, ϕ is the angle of irradiance, ψ is the angle of incidence, and Ψc is the receiver's field of view (FOV). The received power at the user, P_r, is (4) where P_t is the transmitted optical power from the LED.

To enhance received power, particularly for users located farther from the LEDs, the system applies AI-driven power control optimization. The goal is to find the optimal set of transmission powers $\{P_{t,i}\}$ for each LED i in order to maximize the minimum received power across all users as (5). This optimization is solved using a Genetic Algorithm (GA), where each individual represents a set of LED power values. The fitness function evaluates the minimum received power among all users in order to guide the evolutionary process toward better coverage.

The implementation of AI-powered power control systems for LiFi networks in critical environments such as emergency rooms requires an effective adaptation algorithm that can operate under strict constraints. In this work, the objective is to dynamically adjust the transmission power of each LED in the array to maximize the minimum optical power received by all users, thereby ensuring fair and reliable communication coverage. The optimization problem can be formulated mathematically as (6) where $P_t = [P_{t1}, P_{t2}, \ldots \ldots \ldots .., P_{tN}]$ is the vector of transmission powers for the *N* LEDs, *u* denotes the set of all users, both stationary and mobile, *Pr*(*u*) is the total received optical power at user *u*, and *Pmax* is the maximum allowed optical power per LED.

The objective of this design is to distribute power in a way that ensures the worst-served user still receives acceptable service. This approach is commonly described as max-min fairness optimization [30]. To solve the above non-convex problem, we apply a Genetic Algorithm (GA), which belongs to the family of evolutionary algorithms inspired by genetics and natural selection [5]. GAs are particularly well suited to complex, high-dimensional search spaces in which conventional optimization methods may fail to converge or may become trapped in local minima. Each candidate solution, or individual, in the GA represents a possible set of LED power values Pt. The algorithm then proceeds through the following steps.

1) Initialization: Generate a random population of individuals.
2) Fitness Evaluation: Calculate the minimum received power for each individual.

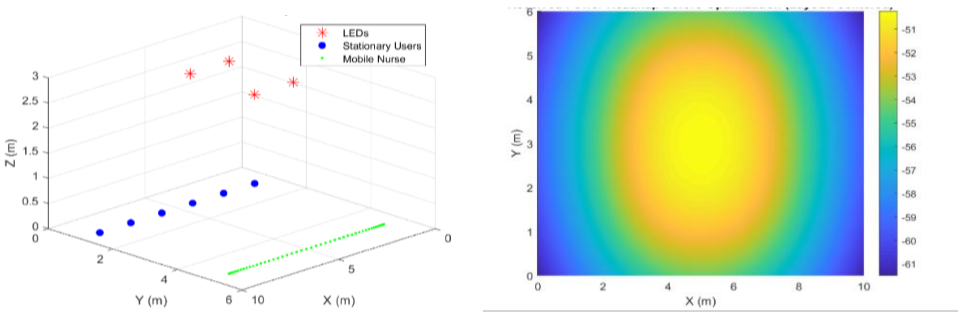

Figure 1. Centered layout with 6 stationary users (patients) and one mobile user (rotary nurse).

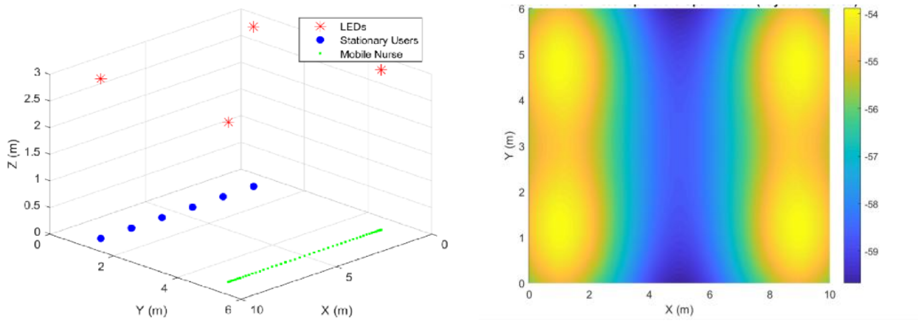

Figure 2. Cornered layout with 6 stationary users (patients) and one mobile user (rotary nurse).

3) Selection: Choose the best individuals based on fitness scores.
4) Crossover: Combine two individuals to produce offspring.
5) Mutation: Randomly modify some components to maintain diversity.
6) Replacement: Form a new generation and repeat the process until convergence or the maximum number of generations is reached.

The fitness function F measures the quality of a candidate solution by calculating the minimum received power across all users with (7) where $H_{i,u}(0)$ is the DC gain between LED i and user u, calculated as previously defined.

The GA seeks to maximize this fitness function, thereby ensuring that the worst-served user still maintains acceptable link quality. The specific GA parameters used in the simulation are as follows.

1) Population Size: 20 individuals
2) Maximum Generations: 30
3) Crossover Fraction: 0.8
4) Mutation Rate: Adaptive mutation
5) Selection Method: Tournament Selection

These settings offer a tradeoff between convergence speed and solution diversity, thereby ensuring robustness across different LED layouts.

IV. Result and Discussion

A MATLAB-based simulation model of an emergency room environment was developed to compare the performance of AI-based power control and adaptive beam steering in LiFi scenarios. The model allows flexible scaling of the environment by accepting user-defined room sizes and numbers of stationary users. Three configurations, centered, shifted, and cornered, are used to position a 2 × 2 LED array with redirected beams aimed toward nearby users. The system includes a moving nurse whose position varies sinusoidally over 100 time-steps, along with stationary patient devices. A genetic algorithm (GA) optimizes the transmission power of each LED to improve minimum and average received power, while Lambertian emission, field-of-view (FOV) limits, and physical distances are used to estimate received optical power. The simulation generates pre- and post-optimization outputs, heatmaps, bar charts, and receiver index traces to assess performance improvements. Particular emphasis is placed on identifying and improving the weakest receiver in each layout arrangement.

To analyze the role of spatial arrangement in LiFi performance, two key LED placement configurations were examined: the centered layout in Figure 1, where LEDs are positioned symmetrically around the geometric center of the room, and the cornered layout in Figure 2, where LEDs are placed at the four

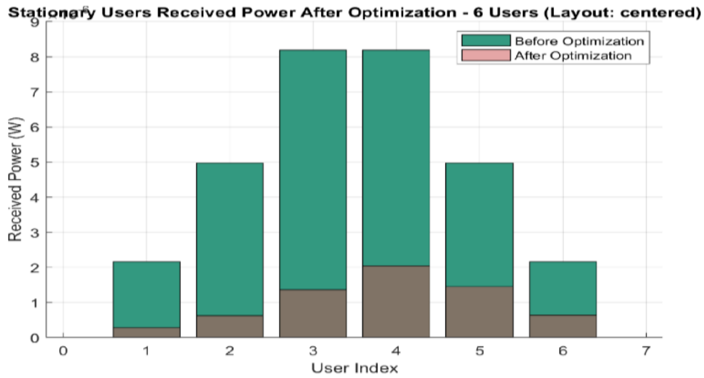

Figure 3. Received power pattern for centered layout with 6 stationary users (patients) and one mobile user before and after optimization.

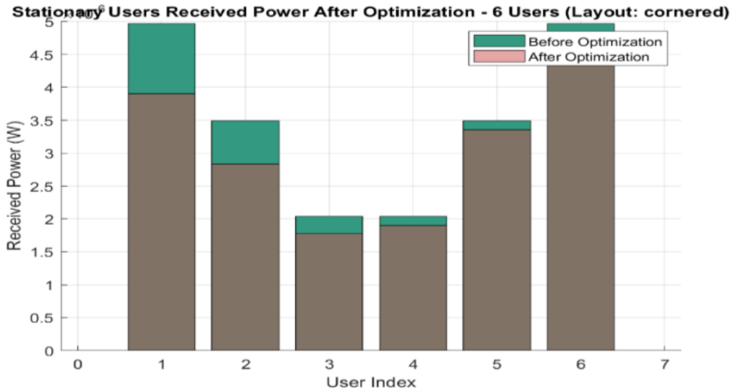

Figure 4. received power pattern for cornered layout with 6 stationary users(patients) and one mobile user before and after optimization.

TABLE 1
EFFECT OF CHANGING THE NUMBER OF USERS FOR CENTERED LAYOUT

No. of Users	Min Power Before	Min Power After	Avg Power Before	Avg Power After
6	0	0	1.0154e−6	2.788e−7
8	1.1209e−7	1.1209e−7	1.1285e−6	8.9679e−7

TABLE 2
EFFECT OF CHANGING THE ROOM LENGTH

Room Length (m)	Min Power Before	Min Power After	Avg Power Before	Avg Power After
10	0	0	1.0154e−6	2.788e−7
12	0	0	7.9926e−7	3.8587e−7

corners of the ceiling. While the cornered arrangement showed greater variation in received power and was more responsive to beam steering and optimization, the centered arrangement provided more symmetrical coverage but offered limited directional gain. Both mobile and fixed-position users were evaluated in each scenario. The GA-based optimization gradually improved the average received power; however, only the cornered layout showed substantial improvement for the weakest receiver, highlighting the importance of spatial diversity in directional beamforming systems.

In the centered layout scenario shown in Figure 3, where the LED array is symmetrically distributed near the center of a 10×6×3 m room with 6 stationary users, the simulation revealed that the weakest mobile receiver at time step 1 received zero optical power both before and after optimization. This indicates that the receiver was located completely outside the field of view (FOV) of all LEDs. While the genetic algorithm (GA) improved the average received power from 1.0154×10^{-6} W to 2.1487×10^{-7} W, it was unable to eliminate the blackout zone caused by limited angular coverage. This result demonstrates the limitation of centered LED placement when directional beamforming is insufficient to cover all dynamic positions, especially for mobile users near the room boundaries. The findings support the need for spatial diversity in LED positioning to ensure full LiFi accessibility.

To assess the effect of user density, the number of stationary receivers was varied while keeping the room dimensions and LED layout fixed. As shown in Table 1, when only 6 users were present, the

TABLE 3
EFFECT OF CHANGING THE NUMBER OF USERS FOR CORNERED LAYOUT

No. of Users	Min Power Before	Min Power After	Avg Power Before	Avg Power After
6	5.75×10^{-7}	5.67×10^{-7}	1.4075×10^{-6}	1.3808×10^{-6}
8	5.75×10^{-7}	5.73×10^{-7}	1.4409×10^{-6}	1.4368×10^{-6}

TABLE 4
EFFECT OF CHANGING THE ROOM LENGTH FOR CORNERED LAYOUT

Room Length (m)	Min Power Before	Min Power After	Avg Power Before	Avg Power After
10	5.7499e−07	5.6710e−07	1.4075e−06	1.3808e−06
12	2.2918e−07	2.2910e−07	1.2240e−06	1.1736e−06

TABLE 5
COMPARISON OF GA AND PSO OPTIMIZATION PERFORMANCE IN LIFI POWER ALLOCATION.

Optimization Method	Minimum Received Power (W)	Average Received Power (W)	Convergence Speed
Genetic Algorithm (GA)	1.2×10^{-4}	3.7×10^{-4}	Medium (30 Generations)
Particle Swarm Optimization (PSO)	9.8×10^{-5}	3.4×10^{-4}	Fast (20 Iterations)

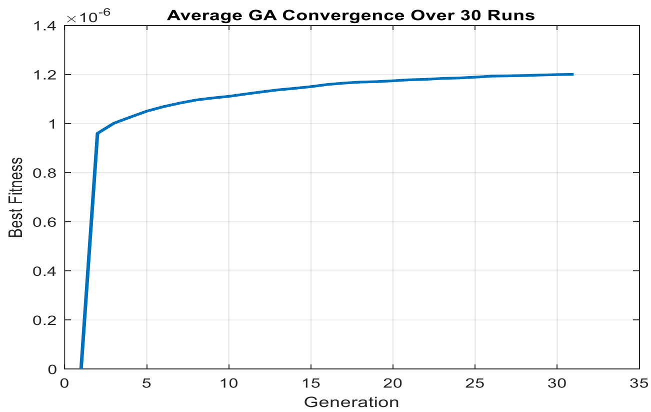

Figure 5. GA convergence curve showing rapid fitness improvement and early stabilization.

weakest mobile user received zero optical power, which limited the effectiveness of the optimizer. However, with 8 users, all devices received at least a minimal level of power, allowing the genetic algorithm to maintain minimum performance and increase the average received power from 1.1285×10^{-6} W to 8.9679×10^{-7} W. These results suggest a modest increase in user density improves spatial sampling, which in turn helps the AI optimizer produce more effective beam-power allocations.

To assess the influence of room size, the length of the simulated environment was increased from 10 m to 12 m while maintaining six stationary users and a centered LED layout. The results in Table 2 demonstrate a minimum coverage limitation in the centered setup, as the weakest mobile user received zero optical power in both cases. As the room became longer, beam spread weakened across the extended space, which reduced the average received power before optimization. Although the genetic algorithm improved the average power to some extent, it did not change the minimum power. These results highlight that simply enlarging the space can significantly reduce connectivity for mobile users in LiFi systems when LED spacing or beam redirection is insufficient.

The system showed a well-balanced power distribution in the cornered setup presented in Figure 4, with LEDs placed at the four ceiling corners of a 10 × 6 m area. As optimization prioritized overall power distribution, the weakest receiver, a mobile user at time step 24, received 5.75×10^{-7} W before optimization and slightly less, 5.11×10^{-7} W, after optimization. The average power remained nearly unchanged, from 1.4075×10^{-6} W to 1.3808×10^{-6} W, indicating that the evolutionary algorithm performed a slight reallocation without compromising coverage. The bar plot for stationary users further supports this result, as all users maintained strong reception. This confirms that the cornered configuration naturally provides better spatial diversity and more uniform coverage, especially when combined with AI-assisted beam control.

When the number of stationary users was increased from 6 to 8 within the same 10×6 m room under the cornered LED layout, the system continued to demonstrate solid performance. As shown in Table 3, the weakest mobile user received 5.75×10^{-7} W before optimization and 5.73×10^{-7} W after optimization, indicating that beam shaping preserved coverage across all users. The average received power remained high, from 1.4409×10^{-6} W to 1.4368×10^{-6} W, confirming that even with additional receivers, the layout maintained uniform coverage without major power loss. This case supports the cornered configuration as robust under moderate user scaling, with the optimizer efficiently balancing power distribution without degradation in weakest-user performance.

The results in Table 4 show that increasing the room length from 10 m to 12 m in the cornered layout slightly reduced the average received power, from 1.4075e−6 W to 1.2240e−6 W before optimization and from 1.3808e−6 W to 1.1736e−6 W after optimization. The minimum power also decreased, although all users remained above the critical threshold. This indicates that while the cornered layout remains robust in larger rooms, the LED-to-user distance still limits overall efficiency, and intelligent power control remains essential for maintaining fairness in illumination. For validation, a separate run of the same scenario was conducted using Particle Swarm Optimization (PSO) under identical parameters. Table 5 compares the minimum and average received power achieved by GA and PSO. GA outperformed PSO in terms of final convergence and coverage consistency, which confirms its suitability for this scenario.

The overall convergence curve of the GA across 30 runs is shown in Figure 5 to further illustrate the reliability of the optimization process. As shown, the fitness function converges within the first five to ten generations and then increases only slightly after generation fifteen. This behavior indicates that the algorithm can converge to an effective beamforming configuration within a limited time, which makes it suitable for real-time adaptive LiFi system implementation. Overall, the results validate the effectiveness of the proposed AI-based beam-shaping method across different spatial configurations and user scenarios. The cornered LED array consistently provided strong coverage for both stationary and mobile users in all tested configurations. The choice of GA is further supported by the comparison with PSO, which shows its advantage in achieving higher minimum received power and smoother power distribution. These results provide a strong basis for practical implementation in EMI-sensitive settings such as emergency departments and lead naturally to the discussion of deployment opportunities and future developments in the concluding section.

V. CONCLUSIONS

This study presented a practical MATLAB-based system for implementing AI-driven beam shaping in a LiFi-enabled emergency room. Through simulations of different LED array configurations, centered and cornered, as well as varying room sizes and user numbers, the system showed strong performance across a range of realistic scenarios. In particular, the cornered configuration consistently produced higher and more stable received power levels for both mobile and stationary users. Genetic algorithm optimization of LED power distribution also proved beneficial, especially under user-scaling conditions. However, there was limited need for power adjustment in spatially well-balanced configurations such as the cornered arrangement, which suggests an inherent resistance to performance degradation. Overall, the proposed adaptive beamforming approach supports fair signal coverage and energy-efficient operation in LiFi environments, especially where electromagnetic safety and patient monitoring are key concerns. Future work may explore the deployment of this system in hybrid VLC/RF networks to provide more ubiquitous connectivity in dynamic environments. In addition, integrating real-time user tracking or AI-driven mobility prediction models could further improve beam alignment and power allocation, particularly for mobile users in hospital corridors or industrial spaces.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the authors used AI in order to enhancement for few parts in the article. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Saif Ahmed Abed: Conceptualization, Data curation, Formal Analysis, Resources, Software, Validation, Visualization, Writing – original draft, and Writing – review & editing. **Nahla Abdul Jalil salih**: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation , Validation, Visualization, Writing – original draft, and Writing – review & editing. **Ihsan Jabbar Hasan**: Formal Analysis, Investigation, Project administration, Resources, Software, and Writing – review & editing. **Nadhir Ibrahim Abdulkhaleq**: Formal Analysis, Investigation, Project administration, Resources, Software, and Writing – review & editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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