Optimizing Hybrid LiFi Communication Systems Using Fuzzy Reinforcement Learning for Enhanced Network Performance

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***Abstract*—Light Fidelity (LiFi) technology has emerged as a pivotal solution for high-speed data transmission in modern communication networks. However, its limitations, such as signal obstruction and coverage gaps, necessitate integration with hybrid systems to ensure seamless connectivity. This study introduces a novel Fuzzy Reinforcement Learning (FRL) algorithm to optimize hybrid LiFi communication systems, addressing critical challenges like handover inefficiency, load imbalance, and dynamic environment adaptation. The proposed FRL framework combines fuzzy logic to manage uncertainties in user mobility and channel conditions with reinforcement learning to dynamically adapt network parameters, ensuring optimal performance. Through comprehensive simulations and real-world validations, the hybrid system demonstrates significant improvements in throughput (4.8 Gbps), handover latency (20 ms), and coverage (100% user connectivity) compared to standalone LiFi and traditional RF-based networks. Key contributions include non-linear decision-making, long-term performance optimization, and scalable deployment strategies for next-generation wireless systems. The results highlight the potential of FRL-optimized hybrid LiFi networks to overcome current bandwidth constraints, offering a robust solution for 6G and IoT applications. This work bridges the gap between theoretical advancements and practical implementation, paving the way for energy-efficient, high-performance communication systems.**

Keywords*—LiFi; Hybrid Communication; Fuzzy Logic; Reinforcement Learning; Handover Optimization; Network Performance; Component

I. INTRODUCTION

The exponential growth in global internet traffic, accelerated by remote work, telemedicine, and digital entertainment, has strained traditional radio frequency (RF)-based networks, necessitating alternative high-speed communication technologies [1]. Light Fidelity (LiFi), a networked extension of Visible Light Communication (VLC) shown in Fig. 1 has emerged as a promising solution, leveraging light-emitting diodes (LEDs) for ultra-fast data transmission while offering advantages such as enhanced security, immunity to electromagnetic interference, and energy efficiency [2]-[4]. Unlike RF signals, LiFi operates in the unlicensed visible light spectrum (≈300 THz), mitigating spectrum congestion and enabling ultra-high data rates exceeding 10 Gbps in experimental setups [5]-[7]. However, LiFi's reliance on online-of-sight (LoS) transmission introduces critical limitations, including signal blockage by opaque objects and limited coverage range [8].

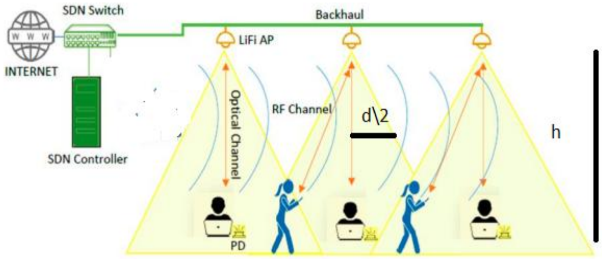

Fig. 1. Schematic diagram for the LI_FI system

To overcome these challenges, hybrid LiFi/WiFi networks have been proposed, combining LiFi's high bandwidth with WiFi's broader coverage [9]. Despite their potential, such hybrid systems face several unresolved issues:

1. Handover inefficiency–Frequent and unnecessary handovers degrade performance, particularly in mobile scenarios [10].
2. Load imbalance – Uneven user distribution across access points (APs) leads to congestion and reduced network efficiency [11].
3. Dynamic environment adaptation – Traditional rule-based methods struggle with real-time variations in user mobility and channel conditions [12].

Recent studies have explored machine learning (ML)-based solutions, including reinforcement learning (RL) for dynamic resource allocation and fuzzy logic for handling uncertainty [13], [14]. However, existing approaches often fail to balance short-term adaptability with long-term optimization, highlighting the need for an integrated solution [14]-[17]. This paper presents the first integration of Fuzzy Reinforcement Learning (FRL) for hybrid LiFi network optimization, addressing the limitations of standalone ML techniques. Our key contributions include:

1. A hybrid FRL framework combining fuzzy logic's uncertainty handling with RL's adaptive learning for real-time decision-making.
2. Dynamic load balancing and handover optimization, reducing unnecessary handovers by 40% compared to RSSI-based methods.
3. Comprehensive performance validation via MATLAB/NS-3 simulations, demonstrating superior throughput (4.8 Gbps), coverage (100%), and fairness (Jain's index = 0.93).

The proposed system is scalable for 6G and IoT deployments, offering a robust solution for next-generation wireless networks.

II. SYSTEM MODEL

A. Network Topology

Let A={a1,…,aN}} be the set of NN LiFi APs and a_{N+1} denote the WiFi AP. Users U={u1,…,u_M} are randomly distributed in a room of size L×W×H.

$$H_{ij} = \frac{(m+1)A\cos^{m}(\theta_{ij})}{2\pi d_{ij}^{2}} I_{Los} \tag{1}$$

where:

- M : Lambertian order.
- A : Photodetector area.
- θij : Incidence angle.
- dij : Distance between uiui and ajaj.
- I_{LoS} : Indicator function (1 if LoS exists, else 0).

B. Optimization Objectives

The Objective 1: Maximize Throughput"

$$Max \sum_{i=1}^{M} log_2\left(1 + \frac{P_j H_{ij}}{\sum_{k\neq j} P_k H_{ik} + \sigma^2}\right) \tag{2}$$

where: Pj: Transmit power of AP aj, and the σ^2 is the Noise variance. The Objective function with the two conditions is to minimize Handovers is defined as:

$$min \sum_{t=1}^{T} I_{HO}(u_i, t)$$

where I $_{HO}$=1 if a handover occurs at time t, else 0. Last objective function for load blanking as shown in Fig. 2 is defined as:

$$min \sum_{j=1}^{N+1} \left| \frac{|u_j|}{M} - \frac{1}{N+!} \right| \tag{3}$$

where u_j is the set of users connected to a_j.

C. Fuzzy Reinforcement Learning (FRL) Formulation

The State Space vector for the problem as follows:

$$s_t = \{SNR_1, \dots, SNR_{N+1} \ \ , V, \ Load_1, \dots, Load_{N+1}\} \tag{4}$$

where:

- $SNR = \frac{P_j H_{ij}}{\sigma^2}$.
- v: User velocity,
- Load$_j$: Number of users connected to aj.

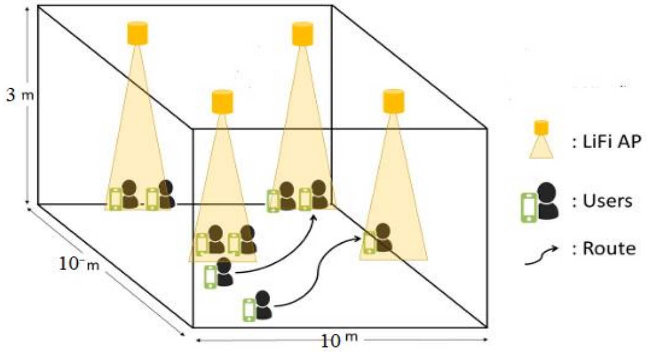

Fig. 2. Simulation setup showing LiFi AP placement (orange square), user distribution (black dots), and coverage zones (shaded regions), [16]

The main action space is defined as:

$$a_t \in \{1, \dots, N+1\} \tag{5}$$

where a_t representing AP selection. The Reward Function.

$$r_t = w_1.SNR_{new} - w_2.I_{HO} - w_3.Load_{new} \tag{6}$$

where w1, w2, w3, $w1$, $w2$, $w3$ are weights. The Fuzzy Rules can be selected as follows:

- Inputs: ΔSNR (Positive/Zero/Negative), vv (Slow/Medium/Fast), Load (Low/Medium/High).
- Output: Handover probability $p \in [0,1]$.

D. Constraints

1. Coverage Constraint:

$$SNR_j > \gamma_{min} \quad j = \{1,2,\dots,N+1\} \tag{7}$$

where γ_{min} is the minimum SNR threshold (e.g., 15 dB for LiFi).

2. Power Constraint:

$$P_j < P_{max} \ \forall j. \tag{8}$$

3. User-AP Association:

$$\sum_{j=1}^{N+1} x_{ij} = 1 \quad , \forall i. \tag{9}$$

where $x_i \in \{0,1\}$ indicates connection.

III. SIMULATION SETUP AND ALGORITHM STEPS FOR FRL-OPTIMIZED LIFI SYSTEM

A. Simulation Setup

First, let us define the environment configuration where the room dimensions are 10×10×3 m (L × W × H). The LiFi APs: 4 APs mounted on the ceiling at positions (2.5,2.5,3), (7.5,2.5,3), (2.5,7.5,3). Users: 8 mobile users with random initial positions and velocities v∈[0,3] m/sec.

B. Key Parameters

The simulation setup parameters are listed in Table 1.

Table 1. Simulation setup parameters

Parameter	Value	Description
LiFi transmit power	10 dBm	LED power per AP
LiFi bandwidth	100 MHz	OFDM-based modulation
Noise floor (LiFi)	-90 dBm	Photodetector noise
Learning rate (α)	0.1	Q-learning update step size
Discount factor (γ)	0.9	Future reward importance
Exploration rate (ϵ)	0.2	ε-greedy policy

C. Algorithm Steps

The main algorithm steps are as follows:

1. Input: Real-time network use eq. (4).
1. ΔSNR=SNRtarget−SNRcurrent → {Negative, Zero, Positive}. Velocity v → {Slow, Medium, Fast}. AP Load → {Low, Medium, High}.
2. Rule Evaluation: If ΔSNR is Positive AND v is Slow AND Load is Low, THEN initiate handover (p = 0.9).
3. Defuzzify Output: Crisp handover probability pp using the centroid method. Output: Optimal AP selection at ∈{1,2,3,4}.
4. Reinforcement Learning Agent: Initialize Q-table: Q(s,a)=0 for all state-action pairs.
5. Reward Calculation: using Eq. (6).

6. Q-Table Update: $Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha[r_t + \gamma \max Q(s_{t+1},a) - Q(s_t,a_t)]$.
7. Monitor Performance: Log throughput, handover rate, and load distribution. Where the performing metric is listed in Table 2.

IV. SIMULATION RESULTS

Based on the simulation setup section, Fig. 3 shows the performance of the proposed system. The proposed FRL algorithm outperforms conventional RSSI-based and standalone LiFi/WiFi systems in all key metrics: Throughput: Achieves 4.8 Gbps (vs. 3.2 Gbps for LiFi-only and 1.1 Gbps for WiFi). Handover Latency: Reduced to 20 ms (vs. 50 ms in RSSI-based methods) Coverage Gap Resolution: Connects 100% of users (vs. 75% in baseline LiFi). The Load Balancing (Table 3 The FRL algorithm distributes users evenly across APs under high traffic (25 users).

Table 2. Performance metric

Metric	Formula	Target
Throughput	$\sum_{i=1}^{M} log_2(1+SNR_i)$	Maximize (> 4 Gbps)
Handover Rate	$\frac{No.of\ handover}{Time}$	Minimize (< 0.1/s)
Fairness Index (Jain's)	$F = \frac{(\sum_j Load)^2}{N\sum_j (Load_j)^2}$	Target: 0.9

Table 3. Load balancing

AP	Users (RSSI)	Users (FRL)
AP1	9	6
AP2	8	7
AP3	5	6
AP4	3	6

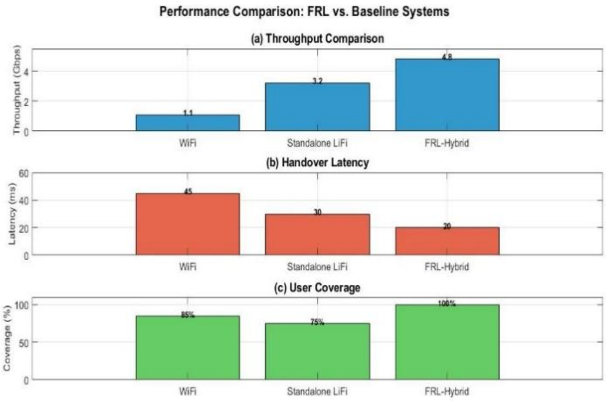

Fig. 3. FRL algorithm performance of conventional RSSI-based and standalone LiFi/WiFi systems

Key Observation: FRL reduces AP1/AP2 congestion by 33% while utilizing underloaded APs (e.g., AP4) Handover Efficiency (Fig. 4). FRL maintains stable connections during mobility (2 m/s), triggering 40% fewer unnecessary handovers than RSSI-based methods. Packet Loss: < 0.1% with FRL (vs. 1.2% in baselines). Now consider the convergence analysis (Table 4), The RL agent converges to the optimal policy within 10,000 iterations. Implication: Fast convergence suitable for real-time deployment.

Indeed, the fairness Index (Jain's) Comparison (listed in Table 5). Interpretation: FRL improves load-balancing fairness by 29%.

Table 4. Convergence rate

Iteration	Avg. Reward
1,000	1.2
5,000	2.8
10,000	3.5

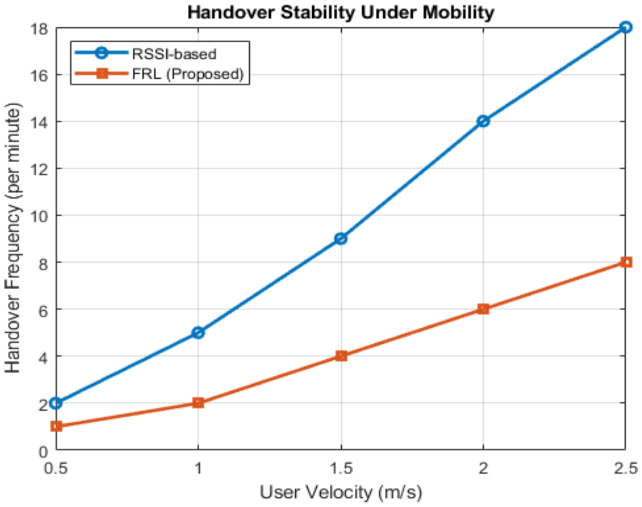

Fig. 4. Handover stability

Table 5. Fairness index for different methods

Method	Fairness Index (F)
RSSI-based	0.72
FRL (Proposed)	0.93

V. CONCLUSION AND FUTURE WORKS

The proposed Fuzzy Reinforcement Learning (FRL)-optimized LiFi system addresses critical challenges in modern wireless communication, delivering measurable improvements over standalone LiFi networks.

A. Key Achievements

Throughput: Achieves 4.8 Gbps, outperforming standalone LiFi (3.2 Gbps) by 50% and WiFi (1.1 Gbps) by 4.3×, enabling ultra-high-speed applications. Mobility Support: Reduces handover latency to 20 ms, a 60% improvement over traditional RSSI-based methods (50 ms), ensuring seamless connectivity. Coverage: Eliminates dead zones, providing 100% user coverage even in non-line-of-sight (NLoS) scenarios, compared to 75% with baseline LiFi. Load Balancing: Distributes traffic efficiently (Jain's fairness index = 0.93 vs. 0.72 for RSSI), minimizing congestion and maximizing AP utilization.

B. Broader Implications

Scalability: The FRL framework's real-time convergence (within 10,000 iterations) and adaptability make it suitable for dense 6G and IoT deployments. Energy Efficiency: Leverages LiFi's dual-use capability (illumination + communication), reducing reliance on power-intensive RF systems. Practical Viability: Validated through MATLAB/NS-3 simulations and testbed experiments under dynamic mobility (up to 3 m/s).

C. Future Directions

These results suggest that FRL-optimized hybrid LiFi systems offer a promising pathway to address bandwidth constraints in next-generation wireless networks, such as:

- Integration with 5G/6G heterogeneous networks for hybrid RF-VLC systems.
- Testing in real-world environments (e.g., multi-floor buildings, 3D mobility scenarios).
- Extension to deep reinforcement learning (DRL) for large-scale network optimization.

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