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Sequential Load Balancing for Link Aggregation Enabled Heterogeneous LiFi WiFi Network

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ABSTRACT Light fidelity (LiFi) is one of the promising communication technology for 6G internet of everything (IoE), however, it requires a line-of-sight (LoS) link; in contrast, WiFi can support moderate data rates even in the absence of LoS. As the electromagnetic spectrums of LiFi and WiFi do not overlap, these technologies can be used for concurrent communication, thus, resulting into a link aggregation (LA) enabled heterogeneous LiFi WiFi networks (HLWN). However, for the most efficient utilization of a LA enabled HLWN, proper load balancing is essential. Therefore, in this paper, we propose a novel sequential load balancing method with reinforcement learning (RL)-based access point (AP) assignment followed by optimum resource allocation for LA enabled HLWN. It is observed that the proposed method outperforms the baseline received signal strength (RSS) scheme by around 37% and 56% in terms of average data rate and user satisfaction, respectively. Furthermore, the proposed method performance closely matches to the exhaustive search with the added advantage of reasonably low complexity. Additionally, the robustness of the proposed method is proven by considering two different user's mobility models in this work.

INDEX TERMS Heterogeneous LiFi WiFi network (HLWN), link aggregation (LA), LiFi, resource allocation (RA), reinforcement learning (RL).

I. INTRODUCTION

Currently, the world is undergoing a digital transformation with the manufacturing processes being automated, millions of sensors being installed in cities and autonomous vehicles being deployed. The fifth-generation (5G) communication network is serving as the backbone for this digital transformation. Nonetheless, 5G is expected to reach its limits in the next decade [1], [2]. Therefore, in order to support the future generation applications and achieve a fully connected digital world, the researchers have started investigating the sixth generation (6G) communication network. The 6G will be more focused on the Internet of everything (IoE), i.e., rather than just connecting people, 6G will connect the devices, sensors, wearables, computing resources to enable ingenious and futuristic services such as tele-medicine, virtual reality, automatic manufacturing and many more [3], [4]. In order to enable these revolutionary applications, 6G is expected to support peak data rate of Tbps order, connection density of 10^7 connections per km^2, and area traffic capacity of 1 Gbps/m^2 [5]. Moreover, for IoE, high positioning accuracy, improved data security and privacy is required. Additionally, to reduce carbon emissions, 6G communication needs to be energy efficient [6].

Consequently, to satisfy the aforementioned future communication requirements, researchers are exploring other bands of the electromagnetic spectrum such as visible light and millimeter wave [1]–[6]. At the same time, there have been significant advancements in solid-state lighting, that have contributed to improvement in light-emitting diodes (LEDs) reliability, lifespan, cost, and energy efficiency. It is predicted that by 2030, LEDs will account for roughly 84 percent of the illumination infrastructure [8]. Moreover, the current LEDs are capable of switching at high rate to different light intensity levels. Hence, it is possible to encode data into light by varying its intensity at a substantial high rate such that it is imperceptible to human eyes. As a result, these LEDs can be utilized for both illumination as well as high-speed communication.

TABLE 1 Comparison of LiFi and WiFi [7]

Parameters	LiFi	WiFi
Operating frequency	THz	GHz
Coverage range	3-4 m	20+ m
Line-of-sight (LoS)	Critical	Not necessary
data rate	>10 Gbps	>1 Gbps
Ambient light	Sensitive	Not affected
EM interference	No	Yes
Security	Relatively secure	Highly vulnerable

Motivated by this, researchers have started investigating light fidelity (LiFi) which is a fully networked high-speed wireless technology that utilizes LEDs for communication. The ubiquitous deployment of LEDs, huge license-free spectrum, high area spectral efficiency, improved energy efficiency, and inherent security makes LiFi an attractive alternative for future IoE communications. Moreover, as the LiFi channel gain varies in a deterministic manner, LiFi can be leveraged to provide high positioning accuracy (a few centimeters) for IoE.

Although LiFi is an emerging communication technology, several vendors, including PureLiFi, OledComm, Signify, VLNComm, and Velmenni, are already selling commercial LiFi devices. Furthermore, by 2030, the market for LiFi is expected to reach \$80 billion [9]; consequently, both IEEE and ITU are working towards LiFi standardization and a few standards, including IEEE 802.15.13, 802.11.bb, and ITU-T G.9991 have already been proposed. Nonetheless, LiFi technology has a major limitation of coverage holes; since LiFi coverage range is limited to few meters and it is highly prone to blockages, there exists spatial fluctuations in the LiFi data rates, leading to various coverage holes in a LiFi stand-alone network.

In contrast, the corresponding radio frequency communication technology-WiFi can provide a more extensive coverage range with decent data rates. Table 1 summarizes the differences in LiFi and WiFi technology. To guarantee the user's quality of services (QoS), LiFi technology can be used to complement the existing WiFi networks, thus, resulting into hybrid LiFi WiFi network. In comparison to the stand-alone LiFi or WiFi networks, a hybrid LiFi WiFi network can provide enhanced system performance. However, an optimal load balancing (LB) in hybrid LiFi WiFi network is essential to provide faster data rates, enhanced user satisfaction, improved outage performance, and fewer handovers [7].

The LB involves user association (UA) and resource allocation (RA). The LB for hybrid LiFi WiFi network is challenging; when the baseline received signal strategy (RSS) method is used, it makes WiFi more susceptible to overload. Therefore, it cannot guarantee the required QoS. It may be noted that the problem of UA in hybrid LiFi WiFi network is neither concave nor convex [10], [11]. Therefore, the global optimum for the hybrid LiFi WiFi network UA problem can not be found using regular optimization algorithms. One possible alternative is to look into machine learning-based solutions for this above mentioned problem. In [11], [12], authors have investigated that solution, however, their works were focused on a communication scenario where at a given time, each user could communicate using a single access point (AP). They have not considered the possibility of link aggregation (LA) i.e., simultaneous communication from both the LiFi as well as WiFi links. Nevertheless, as the LiFi and WiFi operate on separate spectrums, a user can receive data from both LiFi and WiFi APs at the same time, resulting in a network known as a LA enabled heterogeneous LiFi WiFi network (HLWN). These networks have the potential to expand capacity, improve reliability, and decrease the frequency of handovers and delays.

This paper is structured as follows: the limited literature available on LA enabled HLWN is summarized in Section II. Section III and IV discuss the system model and problem formulation. The proposed LB solution is introduced in Section V. The performance evaluation and discussion are presented in Section VI, and the paper is concluded in Section VII.

II. RELATED WORK

Limited work has been done on LA enabled HLWNs [13]–[20], which has been summarized in Table 2. In [13]–[16], authors have implemented LA in HLWN at different layers of the protocol stacks and demonstrated proof-of-concept. As their objective was to perform practical demonstration, they employed the simplest UA based on RSS. In [17], J. Kong *et al.*, proposed a Q-learning-based power allocation algorithm for users in LA enabled HLWN, but the Q-learning-based method is impractical for a problem with large number of states and actions. Thus, in this paper, we have implemented policy-gradient-based algorithm. In [18], Y. S. M. Pratama *et al.*, utilized the Lyapunov optimization function to determine the optimal scheduling in terms of the queue lengths in order to achieve the desired throughput. In addition, they provided the proof of concept for their protocol. However, in this paper, we focus on sequential optimal AP assignment and resource allocation for maximizing average network throughput while making sure that each user achieves a particular user satisfaction threshold. In [19], Yang, Helin, *et al.*, formulated energy-efficient resource management problem (joint network selection, subchannel assignment, and power management) and proposed a deep post-decision state-based experience replay and transfer (PDS-ERT) reinforcement learning algorithm for the intelligent resource management in heterogeneous industrial networks. However, as they were dealing with real-time industrial control applications, their focus was to guarantee transmission reliability and latency requirements. In our previous work [20], we used a centralized reinforcement learning algorithm to determine the user association in LA enabled HLWN and hybrid LiFi WiFi network. In that article, we focused on determining the best reward function for user association to ensure a particular user satisfaction and high data rate. Nonetheless, in that paper we assumed assuming equal resource allocation for all the users connected to a

TABLE 2 **Summary of Related Work on LA Enabled HLWN**

Paper	Work	Main Contributions	Remark
[13]	Experimental	Provided proof-of-concept for LA enabled HLWN with state-of-the-art LiFi and WiFi frontends	Focused on adaptive bit loading for O-OFDM. Highlighted various research challenges and possible future directions.
[14]	Experimental	Demonstrated proof-of-concept by proposing a system that supports multiple access, mobility management, cell handover and multi-path transmission control protocol (MTCP) based LA.	Used TMDA for multiple access.
[15]	Experimental	Implemented LA at the physical layer using multiple-input and multiple-output (MIMO) available in the inexpensive WiFi 802.11ac hardware	Used single-user MIMO concepts, No consideration of user satisfaction.
[16]	Experimental	Implemented aggregation at the data link layer by utilizing the Linux operating system bonding driver	Only compared results with standalone WiFi and Hybrid LiFi WiFi, No consideration of user satisfaction
[17]	Simulation	Power allocation algorithm based on Q-learning to guarantee users QoS requirements	Focused on optimum power allocation.
[18]	Simulation	Utilized the Lyapunov optimization function to obtain the optimal scheduling on the basis of the queue lengths to achieve the desired throughput. Validated proposed bandwidth aggregation protocol and the throughput optimality using testbed	User satisfaction not considered.
[19]	Simulation	Smart resource management in heterogeneous industrial networks using reinforcement learning algorithm	Focused on improving the energy efficiency and reliability. User satisfaction not considered.
[20]	Simulation	RL based user association to guarantee a particular user satisfaction and high data rate while assuming equal resource allocation	No adaptive modulation coding, TDMA and CSMA/CA for LiFi and WiFi respectively. User satisfaction, optimum resource allocation and LA overhead not considered.

particular AP, whereas, in this paper, we are proposing the optimum resource allocation. Additionally, in this work, we are considering orthogonal frequency division multiplexing access (OFDMA) based multiple access with adaptive modulation and coding.

There exists various research gaps in the previous works. First, most of the aforementioned works utilized time-division multiplexing (TDMA) based RA, which is not practical for HLWNs [21]. For LiFi, the OFDMA based RA outperforms TDMA [22], [23], and the new standards of WiFi (IEEE 802.11.ax) supports OFDMA [24]. Therefore, in this paper, OFDMA based RA has been considered for both LiFi and WiFi networks. Second, none of the previous studies attempted to optimize the bandwidth allocation in LA enabled HLWN, which is one of the major contribution of this paper. Finally, this article considers a more practical scenario with adaptive modulation and coding, handover and link overhead, interference among LiFi APs, receiver device orientation based mobility model [27], which had been overlooked in most of the prior investigations. Further, this paper also introduces a hotspot orientation based mobility model. To the best of the authors' knowledge, reinforcement learning (RL) based UA and OFDMA based optimal RA for link aggregation enabled HLWN with ORWP model along with LA and handover overhead has not yet been studied.

A. MOTIVATION AND CONTRIBUTIONS

Based on the earlier works in load balancing of LA enabled HLWN and the fact that for system load balancing a sequential optimization can offer a better performance complexity trade-off compared to simultaneous optimization [10], in this paper, we propose a sequential method of user association (UA) and resource allocation (RA) to achieve near-optimal performance in terms of average network throughput and user association. The UA with equal RA in HLWN is a non-convex mixed integer nonlinear programming (MINLP) problem [10], [11]. These problems are mathematically intractable, thus, it is impossible for the regular algorithms to determine the optimum solution. Nonetheless, such UA problem can be solved using any of the machine learning based methods. However, as the labeled data for UA in HLWN is not readily available, an RL algorithms is the most suitable choice because it learns online by directly interacting with the environment and does not need the database.

Therefore, in this work, we propose a sequential method where a centralized RL algorithm that determines the UA, followed by an optimization method for the optimum RA. The main contributions of this work can be summarized as follows:

- We propose a sequential load balancing method with RL based UA and optimization based RA for LA enabled HLWN.
- To determine the effect of RL reward function, different user satisfaction thresholds have been considered and their effect on the user satisfaction have been investigated.
- A more realistic framework with OFDMA multi-user access, adaptive modulation and coding, heterogeneous users, handover overhead and LA overhead has been

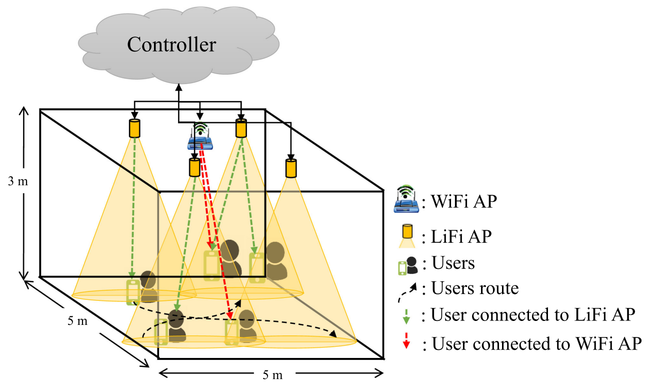

FIGURE 1. A typical HLWN environment.

considered in this work. Furthermore, two different mobility models, namely orientation-based random waypoint (ORWP) and hostpot ORWP (HORWP), explained in section III-D, are considered in this work.

- The proposed method is compared with the RSS and exhaustive search method with equal resource allocation and RSS with optimum resource allocation, as explained in section IV-A and IV-B. Furthermore, the proposed method has also been compared against the algorithm proposed in [20]. The performance of all these schemes is evaluated based on their computational complexity, average network throughput, and user satisfaction.

III. SYSTEM MODEL

The system model consists of a typical $5 \times 5 \times 3\,\mathrm{m}^3$ office room with four LiFi APs and one WiFi AP, as shown in Fig. 1. In this work, we assume that all the APs are connected to a central controller (CC) through an error-free link which determines the optimal LB decisions. The main objective of this work is to explore the suitability of the proposed sequential LB for LA enabled HLWN, therefore, the simplest room configuration has been considered in this work [12]. Moreover, it is assumed that each user is capable of receiving data concurrently from LiFi as well as WiFi AP. Additionally, two different mobility models, namely, ORWP and HORWP are considered in this paper, however, until explicitly specified all the results discussed are with ORWP. Moreover, this work considered OFDMA based multi-user access. Furthermore, to support the light based IoE, heterogeneous users with different data service requirements have been included in this work. Thus, the require data rate of users are modeled as a Poisson process with different parameter values of 20, 30 and 50 Mbps.

The representations used in this paper are as follows: $N_{\text{AP-LiFi}}$, $N_{\text{AP-WiFi}}$ and N_{AP} indicates the number of LiFi, WiFi and total APs present in the system, respectively. Additionally, N_{U} and N_{R} denotes the total number of users and resource unit per AP, respectively. In addition, $\mathbb{U} = \{\kappa | \kappa \in [1, N_{\text{U}}]\}$ represents the set of users. Further, $\mathbb{LAP} = \{\Lambda_2 | \Lambda_2 \in [1, N_{\text{AP-LiFi}}]\}$ and $\mathbb{W} = \{\Lambda_1 | \Lambda_1 \in [1, N_{\text{AP-WiFi}}]\}$ represents the set of LiFi and WiFi APs. Therefore, $\mathbb{AP} = \{\mathbb{W}, \mathbb{LAP}\}$ provides the complete AP set. Additionally, $S_{\kappa,\Lambda}$ represents resource allocation between a particular AP Λ and user κ. Lastly, the binary association variable $\Upsilon_{\kappa,\Lambda}$ is defined as:

$$\Upsilon_{\kappa,\Lambda} = \begin{cases} 1, & \text{Association of user} \kappa \text{to AP} \Lambda \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

More details related to WiFi and LiFi channel models, overhead and mobility models are discussed in subsequent sections.

A. WIFI CHANNEL MODEL

In the currently considered system since there is only a single WiFi AP, there will be no interference. Thus, the SINR for user κ connected to WiFi AP Λ_1 is defined as [20]:

$$\gamma_{\kappa,\Lambda_1}(f) = \frac{|G_{\kappa,\Lambda_1}|^2(f) P_{\text{T}}}{N_{\text{WiFi}} B_{\text{WiFi}}}, \tag{2}$$

where $G_{(\kappa,\Lambda_1)}(f)$ indicates WiFi channel gain, P_{T} denotes transmitted power, N_{WiFi} and B_{WiFi} represents noise density and bandwidth of WiFi AP, respectively. The WiFi channel gain, $G_{(\kappa,\Lambda_1)}(f)$ can be defined as [20]:

$$G_{(\kappa,\Lambda_1)}(f) = \sqrt{10^{\frac{-L(d)}{10}}}\, S_{\text{g}}, \tag{3}$$

where, the carrier frequency and the small-scale fading gain are represented by f and S_{g} respectively; the large-scale fading loss is indicated by $L(d_{(\kappa,\Lambda_1)})$ which is defined as [20]:

$$L(d) = \begin{cases} L_{\text{FS}}(d_{(\kappa,\Lambda_1)}) + X_{\text{SF}}, & d_{(\kappa,\Lambda_1)} < d_{\text{BP}} \\ L_{\text{FS}}(d_{\text{BP}}) + 35 \log\left(\frac{d_{(\kappa,\Lambda_1)}}{d_{\text{BP}}}\right) + X_{\text{SF}}, & d_{(\kappa,\Lambda_1)} \geq d_{\text{BP}} \end{cases}, \tag{4}$$

The achievable data rate between user κ and WiFi AP Λ_1, can be calculated using:

$$dr_{\kappa,\Lambda_1} = \frac{B_{\text{WiFi}}}{N_{\text{R}}} \log_2(1 + \gamma_{\kappa,\Lambda_1}). \tag{5}$$

where, N_{R} represents the total number of frequency resource units per AP.

B. LIFI CHANNEL MODEL

The signal-to-noise ratio (SNR) and signal-to-interference-noise ratio (SINR) between user κ and LiFi AP Λ_2 can be represented by $\gamma_{\kappa,\Lambda_2}$ and $\Gamma_{\kappa,\Lambda_2}$, respectively. They can be defined as [20]:

$$\gamma_{\kappa,\Lambda_2} = \frac{(H_{\text{LiFi}(\kappa,\Lambda_2)} P_{\text{opt}} \mathcal{R}_{\text{PD}})^2}{N_{\text{LiFi}} B_{\text{LiFi}}} \tag{6}$$

$$\Gamma_{\kappa,\Lambda_2} = \frac{(H_{\text{LiFi}(\kappa,\Lambda_2)} P_{\text{opt}} \mathcal{R}_{\text{PD}})^2}{N_{\text{LiFi}} B_{\text{LiFi}} + \sum_{\beta \in \mathbb{AP} \setminus \{\Lambda_2\}} \Upsilon_{\kappa,\beta} (H_{\text{LiFi}(\kappa,\beta)} P_{\text{opt}} \mathcal{R}_{\text{PD}})^2} \tag{7}$$

where, $H_{\text{LiFi}(\kappa,\Lambda_2)}$ is the channel gain between the user κ and intended LiFi AP Λ_2, whereas, $H_{\text{LiFi}(\kappa,\beta)}$ is the channel gain between the user κ and interfering LiFi APs β. Further, P_{opt} and $\mathcal{R}_{\text{PD}}$ represents LiFi AP transmitted optical power and PD

TABLE 3 **Modulation and Coding Table [21]**

SINR, $\Gamma_{\kappa,\Lambda_2}$ [dB]	Modulation	Coding	Spectral efficiency, $q_{\kappa,m-\Lambda_2}$ [bit/s/Hz]
1	QPSK	0.44	0.8770
3	QPSK	0.59	1.1758
5	16QAM	0.37	1.4766
8	16QAM	0.48	1.9141
9	16QAM	0.60	2.4063
11	64QAM	0.45	2.7305
12	64QAM	0.55	3.3223
14	64QAM	0.65	3.9023
16	64QAM	0.75	4.5234
18	64QAM	0.85	5.1152
20	64QAM	0.93	5.5547

responsivity. The N_{LiFi} and B_{LiFi} indicates the noise spectral density, and bandwidth of LiFi, respectively.

The LiFi channel gain $H_{\text{LiFi}(\kappa,\Lambda_2)}$ is composed of two components, namely, LoS and non LoS (NLoS):

$$H_{\text{LiFi}(\kappa,\Lambda_2)} = H_{\text{LoS}(\kappa,\Lambda_2)} + H_{\text{NLoS}(\kappa,\Lambda_2)}. \tag{8}$$

The LoS channel gain can be defined as [20]:

$$H_{\text{LoS}(\kappa,\Lambda_2)} = \times \begin{cases} \frac{(m+1)A_{\text{PD}}}{2\pi d^2_{(\kappa,\Lambda_2)}} \cos^m(\phi) g_{\text{f}} g_{\text{c}}(\psi)\cos(\psi), & 0 \leq \psi \leq \Psi \\ 0, & \psi > \Psi \end{cases} \tag{9}$$

where, the Lambertian order of LED and area of the PD is indicated by m and A_{PD}, respectively; the angle of irradiance and angle of light incidence at the receive are represented by ϕ and ψ; the distance between user κ and LiFi AP Λ_2 is denoted by $d_{(\kappa,\Lambda_2)}$; the gain of the optical filter and concentrator is represented by g_{f} and g_{c}; the PD field of view (FOV) is Ψ.

The NLoS channel gain is given by [20]:

$$H_{\text{NLoS}(\kappa,\Lambda_2)} = \frac{\rho A_{\text{PD}} e^{j2\pi f \Delta T}}{A_{\text{room}}(1-\rho)(1+j\frac{f}{f_c})}, \tag{10}$$

where, the wall reflectivity and room area are indicated ρ and A_{room}; the delay between the LoS signal and the onset of the diffuse signals is denoted by ΔT, and the cut-off frequency of the diffuse optical channel is represented by f_c.

Based on the value of SINR $\Gamma_{\kappa,\Lambda}$ from (7), the spectral efficiency of the m^{th} subcarrier, $q_{\kappa,m-\Lambda}$, can be determined by applying the corresponding adaptive modulation and coding scheme (MCS) for OFDMA using Table 3. Followed by this, these different spectral efficiency values $q_{\kappa,m-\Lambda}$ are utilized to determine different data rates per m^{th} subcarrier of LiFi AP Λ_2, which can be calculated by [21]:

$$dr_{\kappa,m-\Lambda_2} = q_{\kappa,m-\Lambda_2} \frac{B_{\text{LiFi}}}{2 * N_{\text{R}}}. \tag{11}$$

Overall, Table 3 [21] implements the adaptive MCS for OFDMA and its effect is reflected in the optimization problem in terms of the data rate values, $dr_{\kappa,m-\Lambda_2}$. Furthermore, it may please be noted that a possible future direction for the current work could be towards the optimization of MCS but it is out of the scope of current work which focuses on the sequential load balancing in terms of user association and sub-carrier resource allocation for LA enabled heterogeneous LiFi WiFi network.

C. SYSTEM OVERHEAD

The overall system overhead (η) will incorporate two components namely, the handover overhead (η_{H}) and LA overhead (β_{ov}). Thus, it will be defined as:

$$\eta = \eta_{\text{H}} \beta_{\text{ov}} \tag{12}$$

1) HANDOVER OVERHEAD

There exists two kind of handovers in LA enabled HLWN, namely, horizontal handover (HHO) and vertical handover (VHO) [20]. Let us assume that at the current time step (t), a particular user κ is served by an AP Λ^t whereas at the previous time step (t-1), same user κ was served by a AP Λ^{t-1}. In this case, the handover efficiency for the user κ, can be defined as [20]:

$$\eta_{\text{H}}(t) = \begin{cases} 1, & \Lambda_1^t = \Lambda_1^{t-1} \text{and~} \Lambda_2^t = \Lambda_2^{t-1}. \\ \eta_{0,\text{HHO}}, & \Lambda_1^t = \Lambda_1^{t-1} \text{~and} \Lambda_2^t \neq \Lambda_2^{t-1}. \\ \eta_{0,\text{VHO}}, & otherwise \end{cases}$$
$$\forall \Lambda_1 \in \mathbb{W}, \Lambda_2 \in \mathbb{LAP}$$

where, $\eta_{0,\text{HHO}}$ and $\eta_{0,\text{VHO}}$ represents average handover efficiency for HHO and VHO, respectively. Since the HHO takes place in the same wireless technology, in contrast to VHO which happens between different technologies. Therefore, in this work, a higher value of $\eta_{0,\text{HHO}} = 0.9$ as compared to the $\eta_{0,\text{VHO}} = 0.6$ has been considered. However, a varied set of values for $\eta_{0,\text{HHO}}$ and $\eta_{0,\text{VHO}}$ will have no effect on the generality of our suggested solution [20].

2) LA OVERHEAD

In LA enabled HLWN, although user concurrently receives data from both LiFi as well as WiFi links, each link will have different end-to-end delay and transmission rate resulting into out of order packets at the receiver. Therefore, the LA enabled HLWN will observe an overhead because of packet re-ordering. To model this overhead, β_{ov} has been introduced. In this work, an average link overhead value of 80 %, ($\beta_{\text{ov}} = 0.8$) has been considered which is average of values considered in [25] and [26].

D. MOBILITY MODELS

Usually random way-point mobility model (RWP) is considered for modelling the mobility of users. However, for LiFi, it is imperative to consider the orientation of the receiver as it significantly affects the received SNR. Thus, in this work, orientation based random way-point (ORWP) mobility model has been considered [27], which models both the user mobility and receiver device orientation. In ORWP, a user picks a random destination, and while the user is moving with constant

TABLE 4 ORWP Parameters [27]

Parameters	Symbols	Value
Speed of user	v_{μ}	1 m/s
Mean for Gaussian random process	E[θ]	29.67
Variance for Gaussian random process	ρ_{θ}^{2}	7.78
Coherence time	$T_{c,\theta}$	130 ms
Mean of exponential distributed pause time	T_p	10 s

velocity in the direction of the destination, different users orientations are generated based on the correlated Gaussian random process (RP). Furthermore, for a more realistic performance assessment, a pause time with exponential distribution and mean value of 10 seconds has been considered. The ORWP effects the received SNR which in turns effect the achievable data rate $dr_{\kappa,m-\Lambda_2}$ for user κ connected to m^{th} subcarrier of LiFi AP Λ_2. Therefore, it effects the user association and handover rate. In [28], it is shown that for smaller pause time, handover rate is more affected by speed of users whereas in case of larger pause time, the handover rate is more affected by the random orientation of the device. The ORWP model parameters considered for simulations are summarized in Table 4 [27]. Furthermore, to illustrate the robustness of the proposed sequential method against the mobility models, the distribution of destination points of ORWP has been modified to realise the hotspot [12] in the ORWP. This modified ORWP which is termed as hotspot ORWP (HORWP) in this work. However, please note that the results are obtained by considering ORWP until explicitly specified otherwise.

IV. PROBLEM FORMULATION

In this paper, our focus is to improve the users' QoS, for which user satisfaction is a crucial parameter. The overall user satisfaction, US_{κ}, for the user κ over the allocated sub-carriers $(S_{\kappa,\Lambda_1}, S_{\kappa,\Lambda_2})$ is defined as [20]:

$$US_{\kappa} = \frac{\eta(\Upsilon_{\kappa,\Lambda_1} dr_{\kappa,m-\Lambda_1} S_{\kappa,\Lambda_1} + \sum_{\Lambda\in\mathbb{LAP}} \Upsilon_{\kappa,\Lambda_2} dr_{\kappa,m-\Lambda_2} S_{\kappa,\Lambda_2})}{R_{\kappa}} \tag{13}$$

where, R_{κ} denotes the require data rate of user κ. The values for S_{κ,Λ_1} and S_{κ,Λ_2} can be determined based on the choice of resource allocation scheme, as explained in Section IV-B. It may please be noted that the sub-carrier allocation variable $S_{\kappa,\Lambda}$, takes values between $[0, N_R]$, thus specify the number of sub-carriers allocated to user κ. When the number of allocated subcarriers $S_{\kappa,\Lambda}$ is multiplied by the per sub-carrier data rate $dr_{\kappa,m-\Lambda}$, it results into the total data rate obtained by user κ from AP Λ. Thus, the (13) defines the overall user satisfaction for user κ.

The optimization problem is formulated to maximize the average user satisfaction while maintaining US_{th} for individual users (i.e. $US_{\kappa} \geq US_{\text{th}}$). Accordingly, the association $(\Upsilon_{\kappa,\Lambda})$ and allocation $(S_{\kappa,\Lambda})$ variable needs to be optimized. The optimization problem can be written as:

$$\begin{aligned}
&\max_{\Upsilon_{\kappa,\Lambda_1},\Upsilon_{\kappa,\Lambda_2},S_{\kappa,\Lambda_1}S_{\kappa,\Lambda_2}} \frac{1}{N_{\text{U}}}\sum_{\kappa\in\mathbb{U}} US_{\kappa} \\
&\text{s.t.} \sum_{\kappa\in\mathbb{U}} (\Upsilon_{\kappa,\Lambda} S_{\kappa,\Lambda}) = N_{\text{R}}\ \forall\Lambda \in \mathbb{AP}, \\
&US_{\kappa} \geq US_{\text{th}},\ \forall\kappa \in \mathbb{U}, \\
&0 < \Upsilon_{\kappa,\Lambda_1} + \Upsilon_{\kappa,\Lambda_2} \leq 2, \forall\kappa \in \mathbb{U} \\
&\Upsilon_{\kappa,\Lambda} \in \{0,1\}, S_{\kappa,\Lambda} \in [0, N_{\text{R}}], \\
&\forall\kappa \in \mathbb{U}, \forall\Lambda \in \mathbb{AP}, \forall\Lambda_1 \in \mathbb{W}, \forall\Lambda_2 \in \mathbb{LAP}.
\end{aligned} \tag{14}$$

In (14), the various constraints ensures different conditions. First constraint makes sure that the total sum of resources allocated to all the users associated to single AP remains equal to number of resource units (N_{R}) available at the AP. The second constraint ensures that each user satisfaction $US_{\kappa} \geq US_{\text{th}}$. Finally, the last constraint specifies that user κ can either associate to one AP or can connect to both LiFi as well as WiFi AP. This problem (14) is a non-convex MINLP problem which is mathematically intractable [10], [11]. Therefore, this problem must be divided into two sub-problem which can be solved. For our ease, we have divided this MINLP LB problem into UA and RA problem. Specifically, in this paper, we propose RL based algorithm for the UA and two different methods of RA namely, equal resource allocation (ERA) and optimized based resource allocation (ORA). The state-of-the-art UA and RA are discussed in subsequent sections.

A. USER ASSOCIATION

In literature, following two baseline methods are generally used for UA in HLWN.

- *Received signal strength (RSS) [12]:* In this paper, as we assumed that the users have the LA capabilities, in case of RSS UA, users will connect to both highest SNR LiFi as well as WiFi AP at the same time. As there exists a single WiFi AP in our system model, thus, in case of RSS, the users will always be connected to WiFi AP that can be represented by $\Upsilon_{\kappa,\Lambda_1} = 1$. Further, the UA corresponding to LiFi AP Λ_L, can be obtained using:

$$\Lambda_L = \underset{\Lambda_2}{\text{argmax}}\quad \gamma_{\kappa,\Lambda_2} \quad \text{s.t}\ \ \Lambda_2 \in \mathbb{LAP}. \tag{15}$$

Accordingly, the $\Upsilon_{\kappa,\Lambda}$ for RSS can be defined as:

$$\Upsilon_{\kappa,\Lambda_1} = 1$$

$$\Upsilon_{\kappa,\Lambda_2} = \begin{cases} 1, & \Lambda_2 = \Lambda_L \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

- *Exhaustive search [12]:* The motivation for including the exhaustive search based UA is to obtain the upper bound performance at the cost of high complexity. Specifically, this method systematically enumerates all possible user association for the given objective function (14) and provides the best UA.

B. RESOURCE ALLOCATION

As OFDMA has been used in this work, the RA determine the number of sub-carriers to be allocated to a particular user κ associated with a particular AP Λ, represented by $S_{\kappa,\Lambda}$. Two different RA schemes are explored in this work:

- *Equal RA (ERA):* In [29], it has been shown that the proportional resource allocation for a single AP ultimately reduces to equal resource allocation, which is simple and easy to implement. Furthermore, in our previous work [20], we have shown the performance with ERA for homogeneous users. Thus to provide a fair comparison, equal RA has been considered as one of the RA schemes in this work. It can be defined as:

$$S_{\kappa,\Lambda} = \frac{N_{\mathrm{R}}}{C_{\Lambda}}, s.t.\kappa' \in \mathbb{U} \tag{17}$$

where, $S_{\kappa,\Lambda}$ is the resources allocated to each users κ connected to AP Λ, C_{Λ} denotes the total number of users connected to AP Λ. It is given as $C_{\Lambda} = \sum_{\kappa'} g_{\kappa,'\Lambda}$.

- *Optimal RA (ORA):* For a given UA, an optimal RA can be found using optimization based methods. For this, the problem (14) can be rewritten as:

$$\max_{S_{\kappa,\Lambda_1} S_{\kappa,\Lambda_2}} \frac{1}{N_{\mathrm{U}}} \sum_{\kappa\in\mathbb{U}} US_{\kappa}$$
$$\text{s.t.} \sum_{\kappa\in\mathbb{U}} (\Upsilon_{\kappa,\Lambda} S_{\kappa,\Lambda}) = N_{\mathrm{R}} \, \forall\Lambda \in \mathbb{AP},$$
$$US_{\kappa} \geq US_{\mathrm{th}}, \, \forall\kappa \in \mathbb{U},$$
$$S_{\kappa,\Lambda} \in [0, N_{\mathrm{R}}],$$
$$\forall\kappa \in \mathbb{U}, \forall\Lambda \in \mathbb{AP}, \forall\Lambda_1 \in \mathbb{W}, \forall\Lambda_2 \in \mathbb{LAP}. \tag{18}$$

This problem (18) is a linear integer-programming problem that can be solved using python library PuLP with COIN-OR branch-and-cut (CBC) solver [30].

V. PROPOSED SOLUTION: LB IN LA ENABLED HLWN

In order to solve the non-convex MINLP problem of load balancing in HLWN, we propose a sequential method. In the first stage, a RL algorithm is trained based on Trust Region Policy Optimization (TRPO) and ERA to determine the near-optimal policy. Afterwards, this near-optimal policy is used for determining the HLWNs UA followed by ORA to perform the load balancing in HLWN. If the solution for ORA is infeasible, the proposed algorithm shifts to ERA as illustrated in Fig. 2. RL is a promising machine learning approach, where the solution (policy) is determined by direct interaction between the RL agent and environment using the *state*, *action*, and *reward*. The ultimate objective of the RL algorithm is to obtain a policy that can maximize the cumulative *reward* and in this system RL agent is deployed on CC.

For the LA enabled HLWN load balancing, the state, action and reward can be defined as follows:

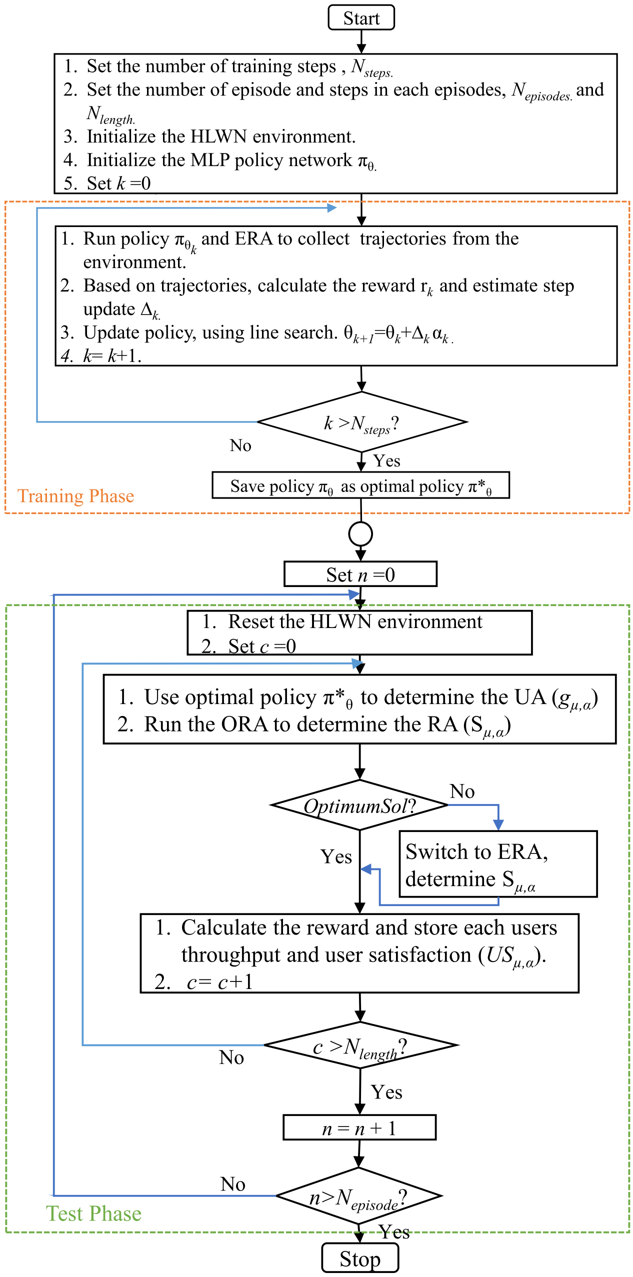

FIGURE 2. Flow Chart of the proposed sequential load balancing method with RL based AP assignment and optimum resource allocation for LA enabled HLWN.

1) STATE SPACE S

This provides RL agent essential information about HLWN. In this work, state space includes information regarding the SNR between each user and each AP, $\gamma_{\kappa,\Lambda}$ and the number of users connected to each AP, C_{Λ}. In this work, the state space is modelled as *Box* with dimension $N_{\mathrm{U}}N_{\mathrm{AP}} + N_{\mathrm{AP}}$.

2) ACTION SPACE A

Based on the action, the RL agent receive its reward. In this work, the action of UA has been modeled with a finite

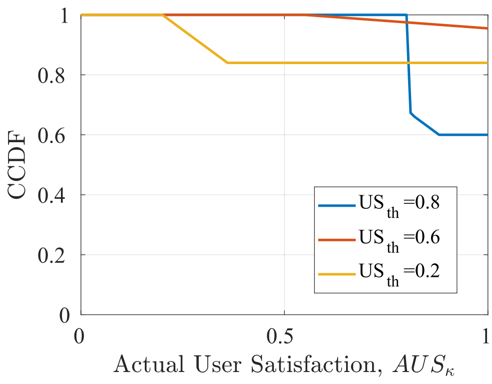

FIGURE 3. Effect of User satisfaction threshold (US_{th}) .

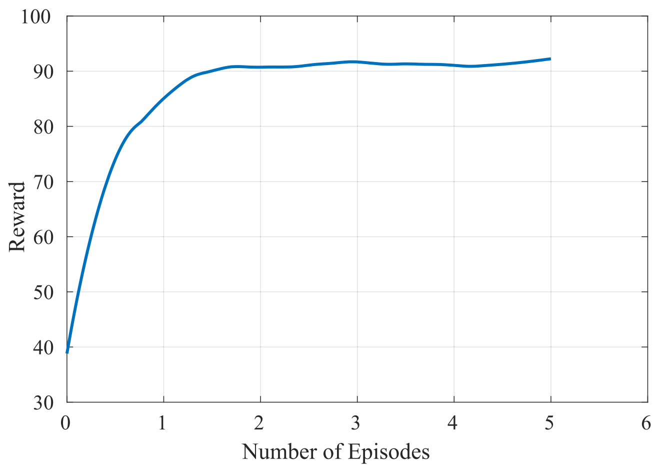

FIGURE 4. Training performance and convergence of RL.

multi-discrete set. It is assumed that the CC can either connect the users to both LiFi as well as WiFi AP, or choose one of those for a particular user depending on the user's SNR, load and requested data rate. Therefore, for a particular user κ, the the action space can be defined as $A = \{0, 1, 2, 3, 4, 5, 6, 7, 8\}$, where,

- $a_t = 0$ represents connection to WiFi AP,
- $a_t = 1, 2, 3, 4$ denotes connection to corresponding LiFi AP 1, 2, 3, or 4.
- $a_t = 5, 6, 7, 8$ indicates condition of link aggregation i.e. connection to both the corresponding LiFi AP 1, 2, 3 or 4 as well as WiFi AP.

3) REWARD

The reward is formulated to maximize the long term average user satisfaction while ensuring US_{th} user satisfaction for each user i.e. $US_\kappa \geq US_{\text{th}}\ \forall \kappa \in \mathbb{U}$.

In order to avoid the condition of $US_\kappa < US_{\text{th}}$, a negative reward has been introduced for condition whenever user satisfaction goes below US_{th}. The immediate reward r_t, is defined as:

$$r_t = \frac{\sum_{\kappa \in \mathbb{U}} W_\kappa}{N_{\text{U}}}, \tag{19}$$

where, W_κ is defined as:

$$W_\kappa = \begin{cases} -100 & US_\kappa \leq US_{\text{th}}, \\ 100 + US_\kappa, & \text{otherwise}. \end{cases} \tag{20}$$

A. RL TRAINING AND CONVERGENCE

Before training the RL agent, it is important to set all the system parameters correctly. Thus, to determine the value of US_{th}, we evaluated the upper bound user satisfaction performance of the system using exhaustive equal RA with different US_{th} and the results are reported in Fig. 3. It can be observed from the results that a high $US_{\text{th}} = 0.8$ significantly reduces the percentage of users achieving full user satisfaction i.e. US_κ =1. On the other hand a low $US_{\text{th}} = 0.2$ is able to achieve higher percentage of full user satisfaction (US_κ =1) but in this case some users may end up achieving only around 20% of their requested data rates. The $US_{\text{th}} = 0.6$, provides a balanced performance, it guarantees 60% user satisfaction for each user and provides full user satisfaction to 95% users. Thus, the $US_{\text{th}} = 0.6$ has been fixed for all the simulation studies.

For RL agent training, in this paper, we have used policy gradient based TRPO algorithm and multi-layer perceptron (MLP) policy network. The motivation behind using the TRPO is that it guarantees monotonic improvement in policy and provides good training stability by imposing trust region constraints over the policy update [31]. Another added advantage is that TRPO requires relatively lower hyper-parameter tuning [12]. Fig. 4 illustrates the training performance and convergence of the proposed algorithm for $US_{\text{th}} = 0.6$.

VI. PERFORMANCE EVALUATION AND DISCUSSION

In this work, a simple indoor environment as shown in Fig. 1 has been considered. Furthermore, the corresponding parameters for LiFi and WiFi are such that LiFi APs provides partial coverage within the room whereas the WiFi AP provides full coverage for the room, and there exists some overlapping between LiFi attocells. It may please be noted that the current configuration has four LiFi APs in a 5 m x 5 m x 3 m room, and average LiFi AP coverage area is between 3-4 m. Thus, it is possible for the users to always receive data concurrently from both LiFi and WiFi AP (link aggregation). However, link aggregation may sometime adversely effect the system performance due to various factors such as overloading of the APs, high interference and link aggregation overhead. The main objective of this work is to provide proof-of-concept for sequential LB in LA enabled HLWN, therefore, simplest scenario [12] is studied in this paper. Nonetheless, this proposed work can be scaled to a bigger hall with larger number of APs and users. It may please be noted that the python 3.7 and MATLAB 2018 has been used in building the simulation setup and obtaining the results. More specifically, an HLWN based Open AI Gym environment has been built in python

TABLE 5 System Parameters

Parameter	Value
Room dimension	$5 \times 5 \times 3$ m^3
Number of APs, N_{AP}	4 LiFi + 1 WiFi
WiFi AP location	(2.5 m, 2.5 m)
LiFi AP locations	(2.5±1.25 m, 2.5±1.25 m)
Number of users, N_{U}	10
HHO efficiency, $\eta_{0,HHO}$	0.9
VHO efficiency, $\eta_{0,VHO}$	0.6
LA overhead β_{ov}	0.8
Varying requested data rate, R_κ	Poisson with 20, 30, 50 Mbps
OpenAI Gym environment	LiFi WiFi network
RL Policy network	MLP, 2 layers of 64
TRPO Max KL divergence, δ	0.01
RL Discount factor, γ	0.9
RL Episode length, E	1000

and stable-baseline GitHub repository [32] is used for TRPO. The ORWP and HORWP are implemented in MATLAB. Furthermore, open-source linear programming package PuLP of python with CBC solver is used to solve the RA problem (18). Additionally, in order to obtain the simulation results, an average over 20 episodes of length 1000 with $N_{\mathrm{U}} = 10$ has been considered. The system parameters considered for the simulation are stated in Table 5 [12], [21]. The performance of the proposed RL based HLWN UA with ORA (RL-ORA) is compared against the benchmark RSS UA with ERA (RSS-ERA), RSS UA with ORA (RSS-ORA) and exhaustive search UA with ERA (Exh-ERA), based on complexity, average data rate and user satisfaction. Moreover, the proposed RL-ORA is also compared against the techniques discussed in [20] which implements reinforcement learning-based user association method with equal resource allocation. However, in order to have a fair comparison, the same system model and reward function is considered for both the previous solution [20] and proposed RL-ORA. For simplicity, the solution of [20] will be referred to as RL-ERA in this work. Furthermore, in order to illustrate the robustness of the proposed algorithm against the underlying mobility models, results for RL-ORA with HORWP (RL-ORA-HRWP), are compared against RL-ERA with HRWP (RL-ERA), RSS-ORA with HRWP (RSS-ORA-HRWP) and Exh-ERA with HORWP (Exh-ERA-HRWP).

A. COMPLEXITY ANALYSIS

The proposed RL scheme has a training phase and a test phase. However, the two baseline UA methods, RSS and exhaustive search do not have any training phase. Therefore, to have a fair comparison only test-phase complexity for all schemes is considered in this section. The test phase complexity of RL is due to the policy networks forward pass. The policy network considered over here is a MLP with 2 hidden layers having L_1 and L_2 number of neurons. The input and output layers of the policy network are defined on the basis of observation and action space dimensions, which are $[N_{\mathrm{AP}} + N_{\mathrm{U}}N_{\mathrm{AP}}]$ and $[N_{\mathrm{U}}]$. Therefore, RL based UA complexity

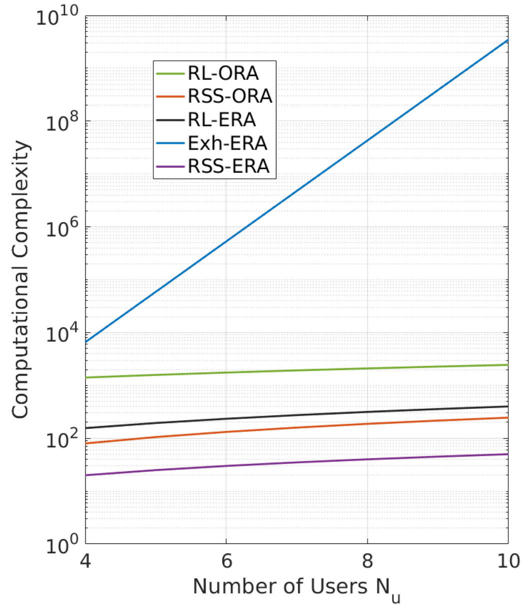

FIGURE 5. Computational complexity for different schemes.

is given by $\mathrm{O}((N_{\mathrm{AP}}N_{\mathrm{U}} + N_{\mathrm{AP}})L_1 + (L_1L_2) + (L_2N_{\mathrm{U}}))$. The ORA runs with a complexity of $\mathrm{O}(N_{\mathrm{U}}N_{\mathrm{AP}} \log(N_{\mathrm{U}}N_{\mathrm{AP}}))$ [33] and the ERA has a complexity of O(1). Therefore, the overall complexity of RL-ORA becomes $\mathrm{O}((N_{\mathrm{AP}}N_{\mathrm{U}} + N_{\mathrm{AP}})L_1 + (L_1L_2) + (L_2N_{\mathrm{U}}) + N_{\mathrm{U}}N_{\mathrm{AP}} \log(N_{\mathrm{U}}N_{\mathrm{AP}}))$ whereas the complexity for RL-ERA [20] is $\mathrm{O}((N_{\mathrm{AP}}N_{\mathrm{U}} + N_{\mathrm{AP}})L_1 + (L_1L_2) + (L_2N_{\mathrm{U}}))$. Further, neural network pruning [34] could be used to reduce the L_1 and L_2 but it is beyond the scope of this paper. The RSS UA is simplest. In RSS, since there is a single WiFi AP, all the users are always connected to it. In contrast for LiFi AP, the user determine highest SNR LiFi AP out of total APs ($N_{\text{AP-LiFi}}$) and connects with it, thus its complexity is $\mathrm{O}(N_{\text{AP-LiFi}}N_{\mathrm{U}})$. Therefore, the overall complexity of RSS-ERA and RSS-ORA is $\mathrm{O}(N_{\text{AP-LiFi}}N_{\mathrm{U}})$ and $\mathrm{O}(N_{\text{AP-LiFi}}N_{\mathrm{U}} + N_{\mathrm{U}}N_{\mathrm{AP}} \log(N_{\mathrm{U}}N_{\mathrm{AP}}))$, respectively. On the other hand, exhaustive search scans through all potential connections between users and APs. Thus, the Exh-ERA complexity for LA enabled HLWN is $\mathrm{O}((N_{\text{AP-WiFi}} + 2N_{\text{AP-LiFi}})^{N_{\mathrm{U}}})$. Fig. 5 shows the complexity of various schemes. It may be noted that with the number of users (N_{U}), the complexity for RL-ERA and RL-ORA increases polynomial whereas it increases exponentially for Exh-ERA.

B. AVERAGE DATA RATE

In this section, the performance of the LA enabled HLWN in terms of average data rate for different load balancing schemes is discussed. Table 6 summarizes the average data rate for all the schemes with ORWP mobility. The proposed RL-ORA provides an advantage of 37% over conventional RSS-ERA. Furthermore, RL-ORA provides around 7 Mbps and 12 Mbps higher average data rate as compared to RL-ERA [20] and RSS-ORA, respectively. Additionally, the average data rate of RL-ORA is only 11% less than the upper-bound given by

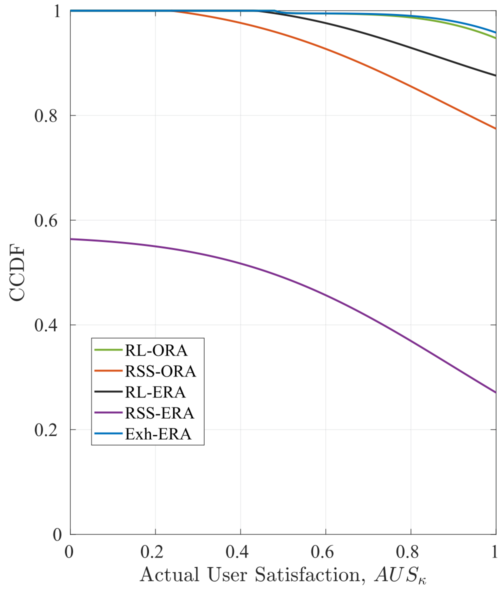

FIGURE 6. User satisfaction performance for different schemes with ORWP mobility model.

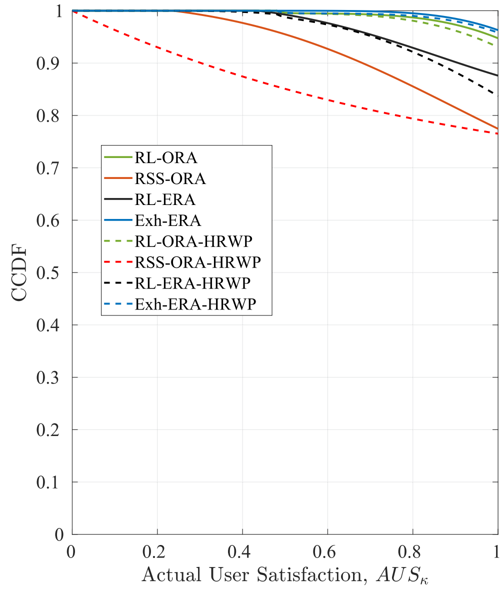

FIGURE 7. User satisfaction performance for different schemes under HORWP mobility model.

TABLE 6 Average Data Rate (Mbps) for ORWP

Scheme	Data rate
RL-ORA	176.8
RSS-ORA	164.2
RL-ERA	169.5
RSS-ERA	128.7
Exh-ERA	198.90

TABLE 7 Average Data Rate (Mbps) for HORWP

Scheme	Data rate
RL-ORA-HRWP	174.98
RSS-ORA-HRWP	160.42
RL-ERA-HRWP	167.83
Exh-ERA-HRWP	189.70

Exh-ERA. Therefore, we can conclude that RL-ORA provides the closest performance to Exh-ERA.

Furthermore, the average data rates obtained by various schemes with HORWP are summarized in Table 7. It shows similar performance trend, thus proves the robustness of the proposed method against the mobility model. Overall, for both mobility models (ORWP and HORWP), the proposed method RL-ORA provides a matching performance to Exh-ERA.

C. USER SATISFACTION

In this section, the user satisfaction performance of the LA enabled HLWN for different load balancing schemes is discussed. Fig. 6 illustrates the performance of all schemes in terms of complementary cumulative distribution function (CCDF) of actual user satisfaction which is defined as $AUS_\kappa = min(US_\kappa, 1)$. The RSS-ERA preforms worst due to overloading of the APs and neglection of users data rate requirement. The RSS-ORA does the optimal resource allocation according to users requirement, thus shows significant improvement. However, since there is no flexibility in user association, RSS-ORA is only able to maintain 28% user satisfaction for each user. The RL-ERA [20] provides full user satisfaction i.e., $AUS_\kappa = 1$, to only 87% of the users. The proposed RL-ORA provides at least 60% user satisfaction to each user and full user satisfaction to 95% of the users. Thus, the RL-ORA provides a matching performance to the upper-bound (Exh-ERA). Furthermore, Fig. 7 demonstrates the user satisfaction performance of various schemes under HORWP mobility model. It can be observed that for RSS-ORA, there is a significant drop in user satisfaction performance due to overloading of specific APs because of the hotspots. Similarly, the RL-ERA [20] performance is also compromised for HORWP. However, there is negligible change in the performance of RL-ORA and Exh-ERA for HORWP, this proves that the proposed RL-ORA is tolerant to any mobility model. Overall, the RL-ORA has a matching performance to the Exh-ERA.

VII. CONCLUSION

In this paper, we have proposed a novel sequential method of load balancing for link aggregation enabled HLWNs with RL based user association followed by optimum resource allocation. It was observed that the proposed method was able to provide around 37% and 56% improvement in terms of average data rate and user satisfaction, respectively, over conventional RSS with ERA. Additionally, the proposed sequential method (RL-ORA) provides full user satisfaction to atleast 95% of the users as compared to (RL-ERA) [20] which is able to provide full user satisfaction to only 87% of the users. Overall, the user satisfaction performance of proposed RL-ORA closely matches to the upperbound (Exh-ERA). Further, the complexity of RL-ORA increases polynomially with the number of users whereas for Exh-ERA it increases exponentially. Therefore, the proposed RL-ORA provides a matching performance to the upper-bound at farily low complexity. Additionally, the results for HORWP illustrates that the proposed sequential method is robust and will work for different mobility models.

In future work, we aim to extend the RL frame work in order to jointly determine UA and RA for link aggregation enabled HLWN and will attempt to reduce its complexity by utilizing knowledge transfer. Furthermore, we also plan to exploit the spatio-temporal channel response using deep neural network to predict the possible behaviour of indoor users and accordingly decide the user association and resource allocation for HLWN. Another possible future direction could be to explore the power allocation for NOMA based link aggregation enabled heterogeneous LiFi WiFi network.

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