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A Novel Method of Combining Decision Making and Optimization for LiFi Resource Allocation

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***Abstract*—Light fidelity (LiFi) is a promising wireless communication technology which can be integrated into existing lighting infrastructure, fulfilling illumination and communication requirements simultaneously. Due to the relatively small coverage area of LiFi with a single access point (AP), a number of LiFi APs are usually needed to provide coverage. However, joint access point selection and resource allocation then become challenging. This issue is mainly tackled using optimization, iteration, and decision making methods. However, the current literature fail to balance the complexity and optimality well. In this paper, a novel approach that combines decision making and optimization is proposed to provide a better trade-off between optimality and complexity. Specifically, a distributed optimization is integrated into the decision making process of fuzzy logic, which is adopted to classify the user based on their channel quality and throughput requirements. Simulation results show that the mixed method can reach the near-optimal achievable throughput, reducing runtime by more than 3 orders of magnitude compared with the global optimization benchmark. Besides, the proposed method is capable of saving up to 72% runtime compared with iteration based benchmark.**

***Index Terms*—Light fidelity (LiFi), load balancing, fuzzy logic, resource allocation**

I. INTRODUCTION

The exponentially upsurging requirements for the data capacity, transmission speed and service quality have aggravated the current radio-frequency (RF) spectrum famine. Due to the inherent fast-switching characteristics of light emitting diodes (LED), visible light communication (VLC) can support illumination as well as the high-speed wireless communication functions at the same time. The network variant of VLC is known as light fidelity (LiFi), which has been recognized as a promising solution to release the spectrum burdens [1]. In contrast to the RF system, LiFi utilizes the extremely wide range of visible light spectrum ($\sim$ 300 THz) with prominent advantages including licence-free, green and safe.

However, LiFi has a relatively small coverage area with a single access point (AP), normally about 2-3 m in diameter. In addition, the LiFi communication link mainly relies on the line-of-sight (LoS) path between the AP and user equipment (UE). As a result, it usually requires a number of APs to ensure the coverage of LiFi networks in an indoor scenario. Meanwhile, the increasing number of indoor UE (e.g. mobile phones, smart wearable devices, integrated sensors, etc.) significantly challenges the process of balancing the traffic loads across multiple APs with low complexity. This load balancing (LB) problem, which is comprised of AP selection and resource allocation, can be solved by the optimization [2], iteration [3-5], or decision making [6], [7] methods. In [2], a centralized optimization algorithm is proposed to achieve the proportional fairness (PF) between UE. It needs a central unit (CU) to control and costs a substantial amount of processing time. To reduce the optimization complexity, the authors in [3] proposed an iterative algorithm which focuses on power allocation for each AP in a hybrid VLC/RF network. In [4], the authors presented an evolutionary game theory (GT) based iterative algorithm to take blockages, random orientation of LiFi receivers and UE data rate requirement into account. Also in [5], the authors reported a reinforcement learning based optimization algorithm to guarantee the quality of service (QoS) in a heterogeneous RF/VLC industrial network. However, the centralized optimization method [2] costs excessive processing power to solve a mixed integer nonlinear problem (MINLP), while the iterative methods [3-5] require a substantial number of iterations to reach the steady state .

Decision making methods are time-saving due to its direct decision characteristic without iterations. The authors in [6] introduced a fuzzy logic (FL) based dynamic LB scheme for the hybrid LiFi and wireless fidelity (WiFi) networks considering UE speed and data rate requirement. However, FL method was only proposed to give an initial assignment and narrow down the search range of the optimisation problem, which is divided into two stages in [6]. In [7], the authors reported a FL-based LB method where the fuzzy rules are set according to statistical knowledge of signal-to-noise ratio (SNR) and data rate requirements. Unfortunately, the FL method in [7] is only borrowed for determining each UE utilizing LiFi or WiFi network, and the remaining UE is also assigned using either the centralised optimization algorithm or signal strength strategy (SSS), which assigns the AP providing the best channel quality to each UE. Moreover, FL brings low computation complexity at the cost of compromised optimality.

To overcome this limitation and reach a better trade-off between the optimality and complexity, we present a novel method combining decision making and optimization for LiFi resource allocation to tackle the UE satisfaction maximization and system throughput improvement in this paper. The mixed decision making and optimization algorithm can reach the near-optimal performance with low complexity. To the best of the authors' knowledge, this is the first time that the joint optimization and decision making method is investigated for

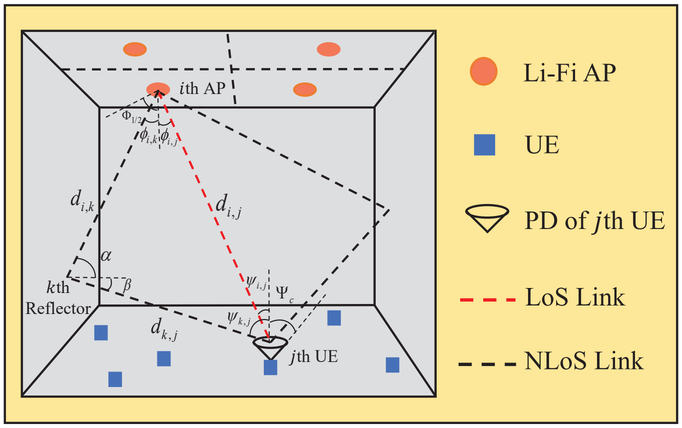

Fig. 1. Indoor LiFi channel geometric model for a case of 4 APs with square topology.

LiFi resource allocation.

The reminder of this paper is organized as follows. The LiFi network model is presented in Section II, including system setup, the LoS and NLoS links. The proposed FL-based LB method is illustrated in the next Section III in detail. Simulation results are shown in Section IV followed by conclusions in Section V.

II. NETWORK MODEL

A. System Setup

In this study, we consider a typical indoor LiFi network in a room with size of $L \times W \times H$ (i.e. length, width and height) that includes varied number of AP and UE. As shown in Fig. 1, the square topology of AP is taken into account for simplicity. Generally, we assume that the number of AP and UE are N_t and N_r, where the APs are fixed at the ceiling of room and the photon detector (PD) is assembled in the smart phone or other detection sensors of UE. Here, the sets of the connectable AP and UE are denoted by $\mathbb{S}$ and $\mathbb{U}$. UE are distributed with a random data rate requirement R_u, which follows an independent identical Gamma distribution with the shape parameter k and the scale parameter θ, thus the expectation of R_u is $k\theta$.

In reality, UE movement always exists thus causing the channel state information of LiFi link is time-varying. However, this dynamic process can be divided into a series of quasi-static periods with tiny time duration, which are defined as 'states'. In each state, every UE can be connected to one AP only, and the number of connectable AP candidates is fixed as 4 due to the channel gain fading for long distance, i.e. each UE can only connect to the nearest 4 APs. For each AP with multiple connections, we consider the time-division multiple access (TDMA) as the multiple access technique. In the indoor LiFi network, there is a CU that determines the AP selections and time resource allocation proportions denoted by $\boldsymbol{X}$ and $\boldsymbol{\rho}$, respectively. Note, each binary $X_{i,j} \in \{0, 1\}$ indicates whether there is a connection between AP i and UE j, and $\rho_{i,j} \in [0, 1]$ denotes the time resource fraction between AP i and UE j.

B. Channel Model

As shown in Fig. 1, we consider not only the LoS, but also the NLoS channel links for the indoor LiFi network. The LoS channel gain denoted by $H^{i,j}_{\mathrm{LOS}}$ can be modeled as a generalized Lambertian radiation pattern [8], formulated as:

$$H^{i,j}_{\mathrm{LoS}} = \frac{(m+1)A_{\mathrm{pd}}}{2\pi d^2_{i,j}} \cos^m(\phi_{i,j}) T(\psi) g(\psi) \cos(\psi_{i,j}), \quad (1)$$

where m is the Lambertian order which satisfies $m = -1/\log_2(\cos(\Phi_{1/2}))$ and $\Phi_{1/2}$ is the LED semi-intensity radiation angle; A_{pd} is the physical area of receiver PD; $d_{i,j}$ is the direct Euclidean distance between the AP i and the UE j; $\phi_{i,j}$ and $\psi_{i,j}$ are irradiance and incidence angles, respectively; $T(\psi)$ and $g(\psi)$ denote the optical filter gain and the concentrator gain, which is defined as:

$$g(\psi) = \begin{cases} \dfrac{n^2}{\sin^2 \Psi_c}, & 0 \le \psi \le \Psi_c \\ 0, & \psi > \Psi_c \end{cases} \quad (2)$$

where n and Ψ_c are the reflective index of the concentrator and the field of view (FOV) of PD, respectively.

For the shown NLoS components in the Fig. 1, it has been shown that NLoS is non-negligible in which the first-order reflections play the biggest role for LiFi network. Here, the surfaces of the room are divided by $\Re$ reflection elements with an area of ΔA. A first-order reflection can be divided into two separate components: a) from AP i to the reflection k on the wall, and b) from reflection k to UE j, where the corresponding Euclidean distances are denoted as $d_{i,k}$ and $d_{k,j}$. Note, each reflection area k is considered as a point source locating at the geometric central point of element k. According to [9], the first-order reflections channel gain can be given by (3). Here, ρ_k is the wall reflectivity, the radiance and incidence angles are $\phi_{i,k}$ and α for the first segment, and β and $\psi_{k,j}$ for the second segment, respectively. Assuming that the emitted optical power of each AP is P_t, the received optical power is generally defined as:

$$P_r = (H^{i,j}_{\mathrm{LoS}} + H^{i,j}_{\mathrm{NLoS}}) P_t. \quad (4)$$

At the receiver, the received photons are converted to electrical current and the corresponding SNR for AP i and UE j can be formulated as:

$$\gamma^{i,j}_{\mathrm{LiFi}} = \frac{(P_r R_{\mathrm{pd}} \kappa)^2}{N_0 B} = \frac{\left((H^{i,j}_{\mathrm{LoS}} + H^{i,j}_{\mathrm{NLoS}}) P_t R_{\mathrm{pd}} \kappa\right)^2}{N_0 B}, \quad (5)$$

where R_{pd} is the detector responsivity; κ denotes the optical to electric conversion coefficient; N_0 is the noise power spectral density and B is the bandwidth of each AP in LiFi system.

III. PROPOSED METHOD

A. FL-based LB Method

The FL method is a generalized decision maker that yields a partial truth value in a certain range instead of giving a hard decision of 'Yes' or 'No' in the standard logic. In general, there are four basic steps in the FL based method: fuzzification, rule evaluation, defuzzification and decision making [10].

$$H_{\mathrm{NLOS}}^{i,j}=\sum_{k=1}^{\Re}\frac{(m+1)\rho_k A_{\mathrm{pd}}\Delta A}{2\pi^2 d_{i,k}^2 d_{k,j}^2}\cos^m(\phi_{i,k})\cos(\alpha)\cos(\beta)T(\psi)g(\psi)\cos(\psi_{k,j}), \tag{3}$$

---

1) Fuzzification: Fuzzy set is different from the ordinary set whose membership function only takes two values of 0 and 1. In this study, each input value $\gamma_{\mathrm{LiFi}}^{i,j}$ and R_j of UE j is represented as three grades: 'Low', 'Medium' and 'High', and they are converted into different crisp values by using a set of membership functions (MFs) [10]. The triangular and trapezoidal functions are applied as MFs, which are defined as:

$$f_{\mathrm{TRI}}(x;a,b,c)=\max(\min(\tfrac{x-a}{b-a},\tfrac{c-x}{c-b}),0)\ , \tag{6}$$

$$f_{\mathrm{TRAP}}(x;a,b,c,d)=\max(\min(\tfrac{x-a}{b-a},\tfrac{d-x}{d-c},1),0)\ , \tag{7}$$

where the functions $\min(\cdot)$ and $\max(\cdot)$ mean that return the minimum and maximum values between the brackets. In this paper, the fuzzified values of three grades for $\gamma_{\mathrm{LiFi}}^{i,j}$ and R_j are given as:

$$V_{\mathrm{SNR}}=\begin{cases}f_{\mathrm{TRI}}(\gamma_{\mathrm{LiFi}}^{i,j};\gamma_{\min},\gamma_{\min},b_1), & \text{for Low}\\ f_{\mathrm{TRI}}(\gamma_{\mathrm{LiFi}}^{i,j};a_1,b_1,c_1), & \text{for Medium}\\ f_{\mathrm{TRAP}}(\gamma_{\mathrm{LiFi}}^{i,j};b_1,c_1,\gamma_{\max},\gamma_{\max}), & \text{for High}\end{cases} \tag{8}$$

and

$$V_{R_j}=\begin{cases}f_{\mathrm{TRI}}(R_j;R_{\min},R_{\min},b_2), & \text{for Low}\\ f_{\mathrm{TRI}}(R_j;a_2,b_2,c_2), & \text{for Medium}\\ f_{\mathrm{TRAP}}(R_j;b_2,c_2,R_{\max},R_{\max}), & \text{for High}\end{cases} \tag{9}$$

where $\gamma_{\min}$, $\gamma_{\max}$ and $R_{\min}$, $R_{\max}$ mean the minimum and maximum values of $\gamma_{\mathrm{LiFi}}^{i,j}$ and data rate requirement of UE j, respectively; a_1, b_1 and c_1 denote the breakpoints of $\gamma_{\mathrm{LiFi}}^{i,j}$ MFs; a_2, b_2 and c_2 represent the breakpoints in the MFs of R_j. In this step, each fuzzified UE introduces 6 crisp values that constitute a fuzzy set.

2) Rule Evaluation: In this process, the crisp values are fed into the rule evaluation table that is heuristic and self-explanatory according to practical indoor LiFi deployment, which is listed in the Table I. For example, for a pair of AP and UE with high SNR and high or medium date rate requirements (Rules 1 and 2), they should probably be connected. However, for those UE with low data rate requirements (Rules 3, 6 and 9), this pair of AP and UE should be kept waiting for exploring better network performance until all other UE are determined no matter SNR is high or low. Each rule uses the AND operator which returns the minimum value. Afterwards, the output value of each rule is obtained, yielding a set of 9 crisp values for each UE.

TABLE I
FUZZY RULES

Rule No.	SNR	Required Rate	State	Selection
1	High	High	Keep	1
2	High	Medium	Keep	1
3	High	Low	Wait	-
4	Medium	High	Keep	1
5	Medium	Medium	Keep	1
6	Medium	Low	Wait	-
7	Low	High	Break	0
8	Low	Medium	Break	0
9	Low	Low	Wait	-

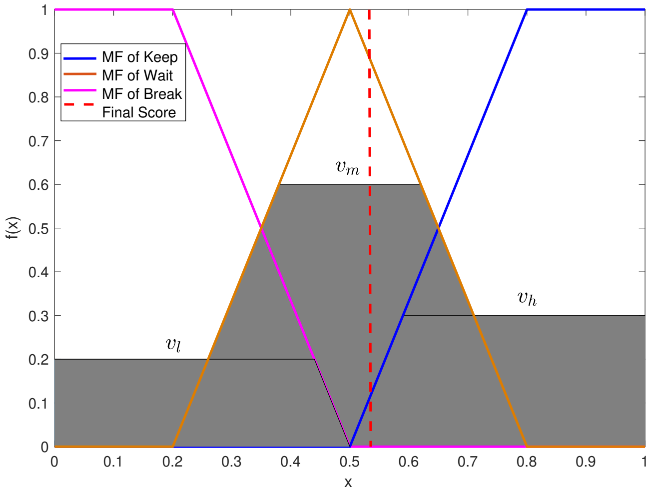

Fig. 2. Defuzzification.

3) Defuzzification: In the defuzzification stage, the final score of a pair of AP and UE is obtained by using the central gravity method [11]. As shown in Fig. 2, the shaded area means the weights of 3 state in the fuzzy logic: 'Keep', 'Wait' and 'Break'. The 'Keep' state means AP i and UE j are connected in a quasi-static period while 'Break' represents no connection. For the state 'Wait', it means the date rate requirement of UE j is so tiny that R_b can be satisfied for an arbitrary connection choice. In the given fuzzy rules, the maximum score of rule 7 to rule 8 for the state 'Break' is denoted as v_l. Similarly, maximum scores of the states 'Wait' and 'Break' are v_m and v_h. Therefore, the final score of a pair of AP and UE can be calculated as:

$$\omega_{i,j}=\frac{\int_0^1 f_{i,j}(x)x dx}{\int_0^1 f_{i,j}(x)dx}, \tag{10}$$

where $f_{i,j}(x)$ is the upper edge function of the shaped area in Fig. 2. Apparently, the final score $\omega_{i,j}$ ranges from 0 and 1, and shows the connection preference for the pair of AP i and UE j, in which bigger the $\omega_{i,j}$ is, more preferable the UE j should connect to the AP i.

4) Decision Making: Finally, by using the output score matrix $\boldsymbol{M}$ with i rows and j columns, we have an initialized

Algorithm 1: FL-based Mixed LB Algorithm

```
Input: $\gamma_{\mathrm{LiFi}}^{i,j}$, $R_j$, $\boldsymbol{M}$
Output: $\boldsymbol{X}$
Initialize $\hat{\mathbb{U}} = \emptyset, \tilde{\mathbb{U}} = \mathbb{U}$;
if $\hat{\mathbb{U}} = \emptyset$ then
    $U_1 \Leftarrow \arg\max_{i\in\mathbb{S}, j\in\mathbb{U}} M_{i,j}$;
    $\hat{\mathbb{U}} \Leftarrow U_1$;
    Remove $U_1$ from $\tilde{\mathbb{U}}$;
    $X_{i,j}|_{\boldsymbol{M}=\max(M_{i,j})} \Leftarrow 1$;
else
    for all UE $j \in \tilde{\mathbb{U}}$ do
        $\boldsymbol{i^*} \Leftarrow \arg\max_{i\in\mathbb{S}}(\sum_{j\in\mathbb{U}} S_{i,j})$ using (14) ;
        if $\boldsymbol{i^*}$ have one element then
            $i^* \Leftarrow \boldsymbol{i^*}$;
        else
            $i^* \Leftarrow \arg\max_{i\in\boldsymbol{i^*}} C_{i,j}$;
        end
        $\boldsymbol{m_j} \Leftarrow M_{i^*,j}$;
    end
    $X_{i,j}|_{\boldsymbol{M}=\max(\boldsymbol{m_j})} \Leftarrow 1$;
    $U_j \Leftarrow \arg\max_{j\in\tilde{\mathbb{U}}} \boldsymbol{m_j}$;
    Remove $U_j$ from $\tilde{\mathbb{U}}$;
end
```

connection preference metrics for $\mathbb{S}$ and $\mathbb{U}$. However, conventional FL based decision maker fail to take the competition of UE into account, thus aggravating the network throughput. In order to avoid the overload of UE, UE satisfaction index $S_{i,j}$ of a pair of AP i and UE j is introduced as:

$$S_{i,j} = \min\{\frac{\rho_{i,j} X_{i,j} C_{i,j}}{R_j}, 1\}, \tag{11}$$

where $C_{i,j}$ is the maximum capacity between AP i and UE j, formulated as:

$$C_{i,j} = B\log_2(1 + \gamma_{\mathrm{LiFi}}^{i,j}), \tag{12}$$

The decision making algorithm follows the following two principles: a) for UE belongs to $\mathbb{U}$, each UE first choose the AP providing the biggest $S_{i,j}$ as candidates; b) for chosen AP candidates, connect a pair of AP and UE with the highest score from $M_{i,j}$. In each step of decision making, the non-allocated and allocated UE are denoted as $\hat{\mathbb{U}}$ and $\tilde{\mathbb{U}}$, respectively. Here, the centralized optimization problem can be formulated as (13), and the distributed optimization problem can be formulated as (14) in the following sub-section. Finally, the proposed mixed optimization and decision making algorithm is summarized in Algorithm 1.

B. Distributed Optimization in the Decision Making Process

In this sub-section, we consider the PF into our problem formulation, given as:

$$\begin{aligned} \max_{\boldsymbol{\rho},\boldsymbol{X}} \quad & \sum_{j\in\mathbb{U}} \log_2(\prod_{i\in\mathbb{S}} S_{i,j}) \\ \text{s.t.} \quad & \sum_{i\in\mathbb{S}} X_{i,j} = 1, \forall j \in \mathbb{U}; \\ & \sum_{j\in\mathbb{U}} X_{i,j}\rho_{i,j} \leq 1, \forall i \in \mathbb{S}; \\ & 0 \leq \rho_{i,j} \leq 1, \forall\, i, j; \\ & X_{i,j} \in \{0, 1\}, \forall\, i, j, \end{aligned} \tag{13}$$

where the operator $\prod_{i\in\boldsymbol{\iota}} x_i$ denotes the repeated multiplication of x_i for all i in its set of $\boldsymbol{\iota}$. In (13), variable $X_{i,j}$ is binary (i.e. integer) while $\rho_{i,j}$ is continuous (i.e. non-integer) and the object function is nonlinear, thus (13) is a MINLP problem. However, it is infeasible to directly solve the MINLP.[1] For a specific case of $\boldsymbol{X}$, a simplified distributed optimization problem for time resource allocation $\boldsymbol{\rho}$ is conducted by using the MATLAB 'fmincon' function, shown as:

$$\begin{aligned} \max_{\boldsymbol{\rho}} \quad & \sum_{j\in\mathbb{U}} \log_2(\prod_{i\in\mathbb{S}} S_{i,j}) \\ \text{s.t.} \quad & \sum_{j\in\mathbb{U}} X_{i,j}\rho_{i,j} \leq 1, \forall i \in \mathbb{S}; \\ & 0 \leq \rho_{i,j} \leq 1, \forall\, i, j, \end{aligned} \tag{14}$$

Without considering the resource allocation part, the computational complexity of the centralized optimization method in (13) is given as $\mathcal{O}({N_{\mathrm{a}}}^{N_{\mathrm{u}}})$. With the SSS method, each UE selects the AP that provides the highest SNR, bringing a computational complexity of $\mathcal{O}(N_{\mathrm{a}}N_{\mathrm{u}})$ [7]. For the SSS-GT method, the complexity can be estimated as $\mathcal{O}(N_{\mathrm{a}}N_{\mathrm{u}}I)$ [4], where I denotes the number of iterations required, which turns bigger with the increase of UE number. The computational complexity of the proposed FL-based method depends not only on the number of inputs K_1 and the number of rules K_2 in the fuzzy logic, but also on the optimization process in decision making step. The big-O complexity of this method can be approximated given as $\mathcal{O}(N_{\mathrm{u}}K_1K_2 + N_{\mathrm{a}}N_{\mathrm{u}})$. Therefore, the proposed method requires a much lower computational complexity than the centralized optimization and iterative algorithms. This will be verified in the next section.

IV. SIMULATION RESULTS

In this section, we conduct the Monte Carlo simulations to evaluate the LiFi network performance of the proposed mixed method. For a fair comparison, we adopt the SSS-GT [4] as an benchmark of iteration based method. The SSS is also chosen as the simplest decision making based benchmark. Due to the exponential increasing runtime of the ES, we can approximately deem the SSS-GT benchmark as the upper bound of performance to analysis. The main simulation parameters are listed in Table II.

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[1] Although it has been shown that the MINLP can be solve by the OPTI toolbox (e.g. BONMIN, SCIP) in [12], nonlinear branch-and-bound algorithm based global optimization solvers take a prohibitive time to return global results, extremely for variables with high dimensions.

TABLE II
SIMULATION PARAMETERS

Parameters	Values
Bandwidth, B	20 MHz
Room height, H	3 m
Room length(width), $L(H)$	5 m and 10 m
AP number, N_t	4 and 16
Shape parameter, k	1
Transmitted optical power, P_t	1.25 W
LED semiangle, $\Phi_{1/2}$	60°
Receiver FOV semiangle, Ψ_c	80°
Optical filter gain, $T(\psi)$	1
Reflection coefficient of walls, ρ_k	0.8
Area of wall reflection elements, ΔA	$0.01\mathrm{m}^2$
Detector area, A_{PD}	$0.0001\mathrm{m}^2$
Detector responsivity, R_{PD}	0.53
Reflective index of concentrator, n	1.5
Optical to electric conversion coefficient, κ	0.8
Noise power spectral density, N_0	10^{-21} A^2/Hz
Fuzzified boundaries of $\gamma_{\mathrm{LiFi}}^{i,j}$: $[\gamma_{\min}, \gamma_{\max}]$	[0, 2500]
Fuzzified thresholds of $\gamma_{\mathrm{LiFi}}^{i,j}$: $[a_1, b_1, c_1]$	[500, 1000, 1500]
Fuzzified boundaries of R_j: $[R_{\min}, R_{\max}]$	[0, 10000] Mbps
Fuzzified thresholds of R_j: $[a_2, b_2, c_2]$	[0, 100, 200] Mbps

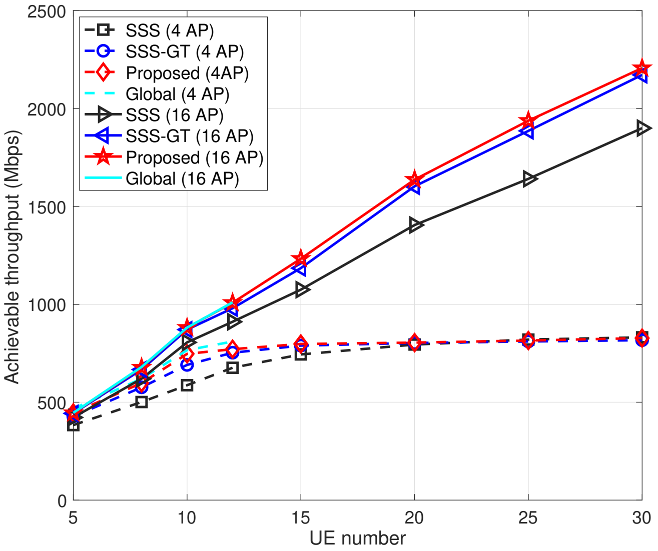

Fig. 3. Achievable throughput versus UE number for the proposed FL-based LB method compared with benchmarks (Due to exponentially increasing complexity of global optimization method, we only simulated with the maximum UE number of 12).

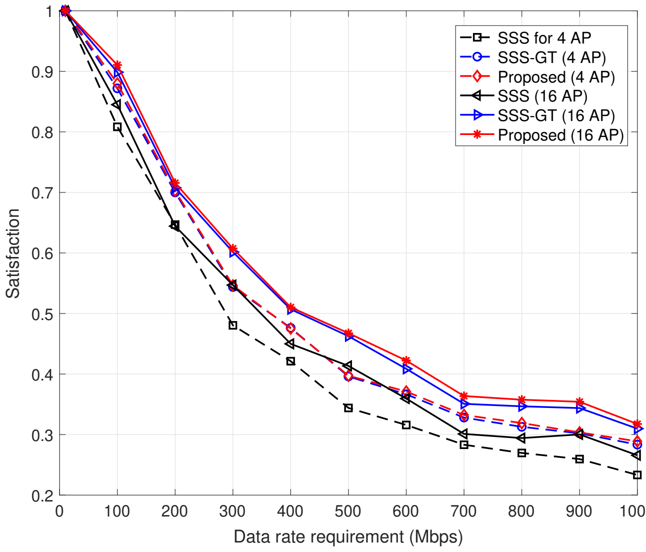

Fig. 4. Satisfaction versus data rate requirement, where the UE number of 4 APs is set as 10 and UE number of 16 APs is 20.

As shown in Fig. 3, we first compare the achievable throughput for indoor LiFi network versus the number of UE for two different scenarios: 4 APs for room size of 5 m × 5 m × 3 m together with a bigger size room of 10 m × 10 m × 3 m having 16 APs. Here the average date rate requirement R_b of UE subjecting to Gamma distribution is set as 100 Mbps. In Fig. 3, the achievable throughput of all curves gradually goes up with the increment of UE number, in which the proposed FL-based LB method achieve the biggest throughput. In the specific 4 APs size, the FL-based method can improve the throughput of SSS from 577 Mbps to 713 Mbps for 10 UE case, and from 795 Mbps to 805 Mbps for 20 UE case, bringing about 23.6% and 1.3% improvement respectively. For another case of 16 APs, the corresponding improvement percentage could be 9.1% and 16.5% for 10 UE and 20 UE. Though the SSS-GT method can reach the local Nash-equilibrium state, the SSS-based initialized state would limit the searching for global optimal results, thus showing a worse than the proposed FL-based LB method.

In addition, the network throughput is not a direct metrics for the associated UE. The satisfaction index with regard to UE date rate requirement is normally confirmed as a key performance indicator (KPI) of quality of experience (QoE). Secondly, we simulate the average satisfaction metrics of UE versus the data rate requirement R_b in Fig. 4. Here we choose the UE number of 10 and 20 as two specific cases in 4 APs and 16 APs. Overall, the satisfaction index declines with the increment of R_b for 4 and 16 APs, that is due to the channel capacity of single LED cell is limited to its fixed bandwidth. In the proposed mixed FL-based LB method, it achieves an approximate satisfaction index for 4 APs case but a better satisfaction performance for 16 APs case. That is because that in (13) the objective function is to maximize the average UE satisfaction.

Fig. 5 depicts the cumulative density function (CDF) curves versus satisfaction for 4APs with 10 UE averaging 100 Mbps and 16 APs with 30 UE averaging 500 Mbps. Note the chosen date rate requirements of 100 Mbps and 500 Mbps, and UE densities are practical KPIs according to the expected QoE in 5G network [13]. Here we deem the SSS as a baseline. In the first case for 4 APs, the FL method has about 87% probability to offer 50% satisfaction index, 75% probability to offer 80% satisfaction index and 65% probability to offer full satisfaction index. Compared with the SSS, the improved

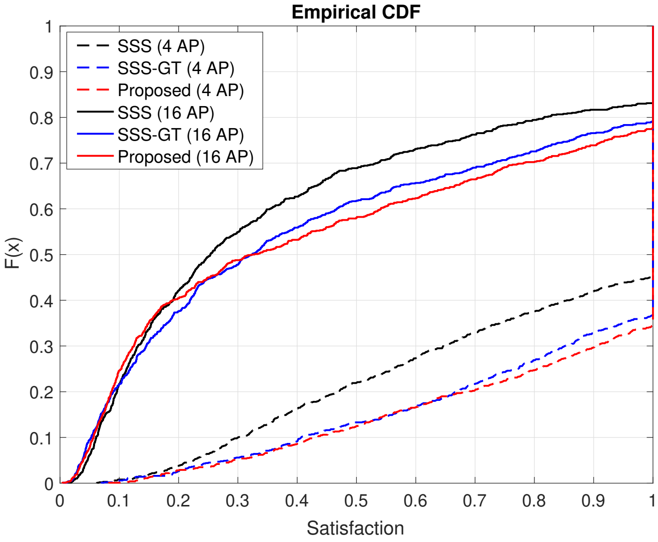

Fig. 5. Comparison of CDF curves for 4 APs and 16 APs cases, where the UE number and R_b are 10 and 100 Mbps for 4 APs case, 30 and 500 Mbps for 16 APs case, respectively.

percentages are 10, 12 and 10, respectively. For the 16 AP case, the FL also has about 42%, 30% and 22% probabilities to achieve 50%, 80% and full satisfaction indexes, showing the satisfaction improvement of 11%, 10% and 7% respectively compared with the SSS baseline. In addition, the proposed FL-based LB method always performs better in satisfaction metrics compared with the SSS-GT based method for 4 APs case and also for 16 APs when satisfaction index surpasses 35%.

Finally, the comparison of runtime between the proposed FL method and benchmarks is listed in Table III. Note it is very time-consuming to give runtime for the global optimization method under large UE number case (i.e. UE number is bigger than 10). Taking an example of 4 AP and 10 UE to illustrate, the runtime of the proposed method can be reduced from 5185 ms to 4.34 ms compared with the global optimization method, which shows that the proposed method reduce runtime by up to 3 orders of magnitude. Similarly, it saves up to 73% runtime compared with iteration based GT method when the case of 16 AP and 30 UE number is considered.

V. CONCLUSION

In this paper, we proposed a novel combined decision making and optimization method for LiFi resource allocation. In the proposed mixed algorithm, the satisfaction index maximization principle for each UE associated with its AP candidates is applied and then the FL-based decision maker offers the pick preference for UE. Compared with the SSS and SSS-GT LB benchmarks, the proposed FL-based LB method can better interpret the input values of SNR and UE date rate requirement using the fuzzy rules. Finally, a better trade-off between complexity and optimality is proved by simulation results, which shows that the complexity can be reduced more than 3 orders of magnitude compared with the global optimization results. Furthermore, up to 73% complexity reduction can be achieved compared with the GT method, together with a slight improvement in network throughput and satisfaction.

TABLE III
COMPARISON OF RUNTIME (IN MILLISECONDS).

Methods \ UE Number		5	10	20	30
4 LiFi AP	SSS	0.000812	0.00130	0.00214	0.00319
	SSS-GT [4]	1.30	2.29	6.46	14.6
	Global	13.7	5185	-	-
	This work	2.54	4.34	9.47	16.4
16 LiFi AP	SSS	0.000918	0.00156	0.00294	0.00409
	SSS-GT [4]	2.22	7.80	35.4	66.6
	Global	5210	-	-	-
	This work	2.62	4.67	10.1	17.8

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REFERENCES

[1] X. Wu, M. D. Soltani, L. Zhou, M. Safari and H. Haas, “Hybrid LiFi and WiFi Networks: A Survey”, *IEEE Commun. Surv. Tutor.*, vol. 23, no. 2, pp. 1398-1420, Feb. 2021.

[2] X. Li, R. Zhang, and L. Hanzo, “Cooperative load balancing in hybrid visible light communications and WiFi”, *IEEE Trans. Commun.*, vol. 63, no. 4, pp. 1319–1329, Apr. 2015.

[3] M. Obeed, A. M. Salhab, S. A. Zummo and M. Alouini, “Joint Load Balancing and Power Allocation for Hybrid VLC/RF Networks”, in *2017 IEEE Global Communications Conference*, 2017, pp. 1-6.

[4] Y. Wang, X. Wu, and H. Haas, “Load balancing game with shadowing effect for indoor hybrid LiFi/RF networks”, *IEEE Trans. Wireless Commun.*, vol. 16, no. 4, pp. 2366-2378, Apr. 2017.

[5] H. Yang, A. Alphones, W. -D. Zhong, C. Chen and X. Xie, “Learning-Based Energy-Efficient Resource Management by Heterogeneous RF/VLC for Ultra-Reliable Low-Latency Industrial IoT Networks”, *IEEE Trans. Ind. Informat.*, vol. 16, no. 8, pp. 5565-5576, Aug. 2020.

[6] X. Wu and H. Haas, “Load Balancing for Hybrid LiFi and WiFi Networks: To Tackle User Mobility and Light-Path Blockage”, *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1675-1683, Mar. 2020.

[7] X. Wu, M. Safari and H. Haas, “Access Point Selection for Hybrid Li-Fi and Wi-Fi Networks”, *IEEE Trans. Commun.*, vol. 65, no. 12, pp. 5375-5385, Dec. 2017.

[8] H. Ji, T. Zhang, S. Qiao and Z. Ghassemlooy, “Joint Dimming Control and Optimal Power Allocation for THO-OFDM Visible Light Communications”, *IEEE Trans. on Commun.*, vol. 69, no. 8, pp. 5352-5366, Aug. 2021.

[9] J. M. Kahn and J. R. Barry, “Wireless infrared communications”, *Proc. IEEE*, vol. 85, no. 2, pp. 265–298, Feb. 1997.

[10] L. A. Zadeh, and R. A. Aliev, “Fuzzy logic theory and applications: part I and part II”, *World Scientific Publishing*, 2018.

[11] H. Burchardt, S. Sinanovic, Z. Bharucha, and H. Haas, “Distributed and autonomous resource and power allocation for wireless networks”, *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2758–2771, Jul. 2013.

[12] P. Belotti, C. Kirches, S. Leyffer, J. Linderoth, J. Luedtke, and A. Mahajan. “Mixed-integer nonlinear optimization”, *Acta Numerica*, 22, pp. 1-131, 2013.

[13] Samsung 5G vision white paper, Feb. 2015. Available at: https://www.samsung.com/global/business/networks/insights/white-papers/5g-vision/