Scheduling with Heterogeneous QoS Provisioning for Indoor Visible-light Communication

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Visible-light communication (VLC) combined with advanced illumination can be expected to become an integral part of next-generation communication networks. One of the major concerns in VLC implementation is developing resource-allocation schemes in a multi-user scenario. However, the scheduling for heterogeneous quality of service (QoS) traffic has not been studied so far, for the indoor VLC downlink system. In this paper, we creatively introduce effective-bandwidth and effective-capacity theory into the multi-user scheduling (MUS) problem, to guarantee the user's statistical delay QoS. We also take account of the aggregate interference (AI) in the indoor VLC downlink system, and analyze its impact on the user-centric MUS problem for the first time. Simulations show that the AI has a nonnegligible influence on the scheduling result, and that the proposed scheduling scheme could guarantee the user's QoS requirement under the premise of ensuring sum capacity.

I. INTRODUCTION

Owing to huge unlicensed bandwidth, high data-rate potential, energy-efficient illumination, etc., research on visible-light communication (VLC) has been intensifying for the past few years [1]. A high data rate of about 3-4 Gbps has been achieved in the point-to-point scenario [2-4]. Furthermore, in the multitransmitter-multireceiver scenario, multiple users could be served simultaneously, and multiple access points (APs) could be designed to improve received-signal strength. It is clear that the research emphasis of VLC is evolving to studies of networking. In a multi-user scenario, several transmitters are needed to cover the whole communication area, which may cause severe interuser interference. As shown in Fig. 1, when AP 3 is assigned to user 1 for communication, user 2 would suffer severe interuser interference. Similarly, there is interuser interference between users 2 and 3. Therefore, a proper scheduling
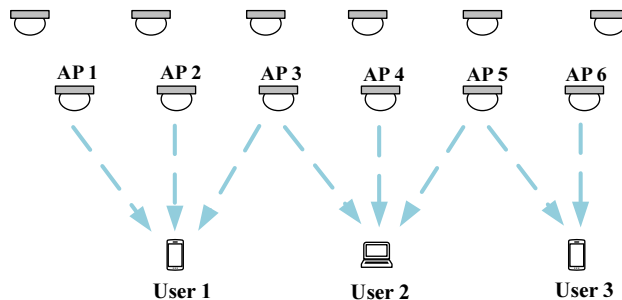

FIG. 1. An indoor VLC downlink network.

algorithm is needed to address this problem, while achieving high sum capacity and good user fairness.

So far, since studies of scheduling and resource allocation in a multi-user VLC downlink system are still at the initial stage, not much research has been published on these topics, especially for multitransmitter-multireceiver scenarios. The

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authors in [5] studied different cell-formation schemes and proposed the user-centric scheduling algorithm to eliminate the interuser interference in an amorphous cell. Targeting at maximization of the system's sum rate while taking into account user fairness, the authors in [6] proposed an efficient resource-allocation method to overcome interuser interference based on graph theory. In [7], the user-centric design of VLC for heterogeneous networks was presented. To solve the scheduling problem for multiple moving users, a user-centric scheduling scheme was proposed to introduce a time-division scheduling framework in [8]. At the basis of the user-centric scheduling algorithm, the authors in [9, 10] proposed a multi-user scheduling (MUS) scheme to improve system capacity. Compared to the previous user-scheduling scheme, the user-centric scheduling algorithm can achieve higher sum capacity and better fairness because the interuser interference caused by direct light is eliminated.

For a communication user in a given time slot, the aggregate interference (AI) of the multiple cells' reflected light has a nonnegligible influence on its scheduling priority for the next time slot. However, the user-centric MUS algorithm in all studies [5-10] did not take account of the AI. At the same time, we also notice that these works only endeavored to achieve high sum rates and a better user fairness, based on a proportional fairness (PF) scheduling scheme, but not considering the user's quality of service (QoS) requirement. For example, one user is browsing the Web, which has a looser QoS requirement, while another user in the room is watching a video, which has a more stringent QoS requirement. In this case the users do not need equal scheduling opportunity.

To solve the two aforesaid two problems, in this paper we analyze the impact of AI on the MUS problem and propose a scheduling scheme with heterogeneous QoS provisioning for the indoor VLC MUS problem. First, we solve the user-centric MUS problem based on an interference-graph model. Next, we analyze the impact of reflected light from multiple cells on the user-centric MUS problem for the first time. Then, we creatively propose a scheduling scheme that can guarantee the user's statistical delay QoS, on the basis of effective-bandwidth and effective-capacity theory. A user with a more stringent QoS requirement will obtain more scheduled times through our heterogeneous QoS-based scheduling scheme. Simulation shows that the influence of AI on the MUS problem cannot be ignored, and that the proposed heterogeneous QoS-based scheduling scheme can guarantee the heterogeneous QoS requirement under the premise of sum capacity.

The rest of this paper is organized as follows: Section II gives the downlink system model. Section III provides the solution to the user-centric MUS problem, and analyzes the influence of AI while researching the scheduling scheme with heterogeneous QoS provisioning. Section IV presents the simulation results, and conclusions are drawn in Section V.

II. SYSTEM MODEL

2.1. Link Characteristics

A downlink VLC system is considered, which is constituted by a set of VLC APs, each relying on an array of several LEDs. Since each user has a limited field of view (FOV), each can only receive information from the optical APs when at least one AP resides in the user's FOV. According to [11], if the angle of incidence ψ from an AP to a user is smaller than the user's FOV ψ_F, then the optical channel's direct-current (DC) attenuation of the line-of-sight (LOS) path is given by

$$H(0) = \frac{(w+1)D_{PA}}{2\pi L^2} \cos^w(\varphi) T_s(\psi) g(\psi) \cos(\psi) \qquad (1)$$

where D_{PA} is the physical area of the detector in the photodiode (PD), L is the distance between transmitter and receiver, ψ is the angle of incidence, φ is the angle of irradiance, $T_s(\psi)$ is the gain of the optical filter, w is the order of Lambertian emission (which is given by the semiangle $\Phi_{1/2}$ at half illumination of the source, and can be calculated as $w = -(\ln 2)/\ln\left[\cos(\Phi_{1/2})\right]$), and the gain of the optical concentrator $g(\psi)$ can be given as $g(\psi) = a^2/\sin^2 \psi_F$, where a denotes the refractive index.

Furthermore, according to [12], when the incidence angle ψ is no larger than ψ_F, the channel's DC attenuation of the first reflection is given by

$$dH_{ref}(0) = \frac{(w+1)D_{PA}}{2\pi L_1^2 L_2^2} \rho dA_{wall} \cos^w(\varphi)\cos(\beta_1)\cos(\beta_2)T_s(\psi)g(\psi)\cos(\psi)$$

$$(2)$$

where L_1 is the distance between the AP and the reflective point, L_2 is the distance between reflective point and receiver, ρ is the reflectance factor, dA_{wall} is the reflective area, φ is the angle of irradiation of the LED, β_1 is the angle of irradiance to the reflective point, β_2 is the angle of irradiance to the receiver, and ψ is the angle of incidence.

2.2. Problem Formulation

Our goal is to find the optimal scheduling policy for maximizing the system's sum capacity and scheduling the users in a fair manner, while guaranteeing the heterogeneous QoS requirement.

We suppose that there are K users and N APs in a square room. Let U be the set of users and C be the set of APs, where $U = \{u_i \mid i = 1, 2, \ldots, K\}$ and $C = \{AP_j \mid j = 1, 2, \ldots, N\}$. For a scheduled user i, several APs within the FOV are chosen from C to form a virtual cell (VC). Controlled by a central station, the APs in a VC send identical signals to its user simultaneously, to improve the strength of the received optical signal. To eliminate the interuser interference, the VCs are independent from each other in a given time

slot. As shown in [13], the PF scheduling mechanism can achieve a high sum capacity and good user fairness, with the priority factor of the PF scheduler given as

$$p_i^{(t)} = \frac{r_i^{(t)}}{R_i^{(t)}} \tag{3}$$

where $r_i^{(t)}$ denotes the achievable data rate and $R_i^{(t)}$ denotes the long-term average channel rate for time slot t. $R_i^{(t)}$ is the average channel rate of user i over a past time interval of length T_F, and is refreshed by

$$R_i^{(t)} = \begin{cases} \left(1 - \dfrac{1}{T_F}\right) R_i^{(t-1)} + \dfrac{1}{T_F} r_i^{(t-1)}, & \text{if scheduled} \\[3mm] \left(1 - \dfrac{1}{T_F}\right) R_i^{(t-1)}, & \text{if not scheduled} \end{cases} \tag{4}$$

Based on the PF scheduling mechanism, we introduce a user's effective bandwidth into the priority factor p to guarantee the user's statistical delay QoS in the indoor VLC MUS problem. The details of our proposed heterogeneous QoS-based scheduling scheme are presented in subsection 3.3.

Therefore, our MUS problem may generally be formulated as

$$\begin{aligned} \max \quad & \sum_{i=1}^{K} p_i^{(t)} \\ \text{s.t.} \quad & VC_i \cap VC_j = \phi, \quad i,j = 1,\dots,K, \ i \neq j \qquad (5) \\ & \bigcup_{i=1}^{K} VC_i \subset C \end{aligned}$$

For each time slot the scheduling process is to select communication users without interuser interference, and form multiple VCs.

III. PROBLEM SOLUTIONS

3.1. Solution to the User-centric MUS Problem

The communication-user set can be determined for a given time slot by solving the nondeterministic-polynomial (NP) -complete problem Eq. (5), but this cannot be achieved within an acceptable run time. Therefore, in this subsection we build a graph model to choose communication users while avoiding interuser interference, based on the simple and efficient greedy algorithm [6].

For interuser interference that can be represented by the relationship of vertices, a graph model can be generated to solve the NP-complete problem. According to the layout of APs and users, we build an undirected graph $G(V, E)$, which could be called an interference graph, as shown in Fig. 2. The vertex set $V(G)$ of the interference graph is the

user set U. The edge set $E(G)$ is determined by the interuser interference. If users i and j have the same APs in their FOVs, there will be an edge between vertices i and j, i.e. the solid line in Fig. 2. At this time, the two vertices are referred to as neighbors, and $I(v_i)$ is the set of neighboring vertices of v_i. We use $d(v_i)$ to denote the number of neighboring vertices for v_i, which is the degree of v_i. Otherwise, the two vertices are not connected.

Since the placement of the APs is fixed, the edge set $E(G)$ is determined by a user's specific conditions, such as position and FOV. Therefore, the MUS problem is said to be user-centric.

To eliminate interuser interference, the MUS problem can now be transformed into another problem in the weighted interference graph: that of choosing a set of vertices with maximum sum weight while assuring that any two of them are not connected. This is actually a maximum-weighted independent-set problem (MWISP). From [14], the min-greedy algorithm is used to solve the MWISP. According to the min-greedy algorithm, a vertex of higher degree has more neighboring vertices, which makes it less likely to be in a maximum-weighted independent set (MWIS). For each time slot, we add the vertex v_i with minimum degree $d(v_i)$ into
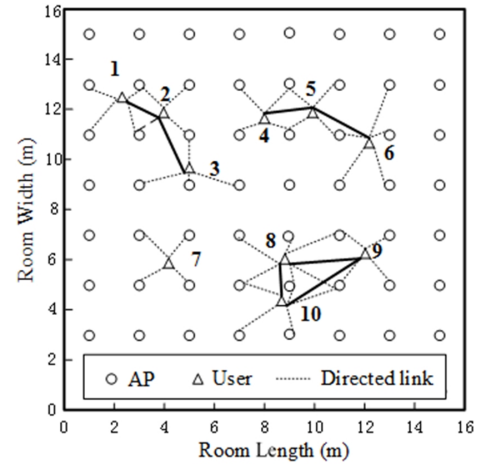

FIG. 2. Interference graph.

TABLE 1. User-centric MUS algorithm

User-centric MUS algorithm
1: **for** each time slot t **do**
2:    $MWIS = \phi$, $V(G) = U$;
3:    **while** $V(G) \neq \phi$ **do**
4:      find $v_i = \arg\max\left(\dfrac{p_i^{(t)}}{d(v_i)+1}\right)$, $v_i \in V(G)$;
5:      $MWIS = MWIS \cup v_i$;
6:      $V(G) = V(G) \backslash (v_i \cup I(v_i))$;
7:    **end while**
8: **end for**

MWIS, and then remove it and its neighbors from the whole set of vertices. Then the graph is updated and we repeat this process until no vertex is in the interference graph. As for our user-centric MUS algorithm, the weight of the vertex, i.e. its priority factor p, is also taken into consideration.

The procedure of the user-centric MUS algorithm is described in Table 1.

3.2. Analysis of AI

In this part, we will analyze the impact of the AI on the user-centric MUS algorithm for the indoor VLC downlink system.

For a given time slot, all of the chosen VCs are independent of each other, as the user in the VC under consideration cannot receive LOS interference power from other VCs. The power of the reflected light is small enough, compared to that of the direct light. However, when a number of users form their own VCs in a time slot, the cumulative interference from the reflected light of other VCs is not negligible. We call this AI. Figure 3 gives the scheduled user set and corresponding VCs for a time slot. As shown in Fig. 3, the scheduled user in VC_5 receives reflected interference power from four APs in VC_6. Similarly, the APs in other VCs also generate reflected interference for the scheduled user in VC_5. Therefore, the scheduled user in VC_5 receives aggregate interference power from five other VCs.

According to [12], a large fraction of the reflected power is due to the first reflection. herefore, in this paper we study the impact of AI on the scheduling result, considering only the first reflection. When considering the impact of AI, the signal-to-interference-plus-noise ratio (SINR) of user i is defined as

$$\xi_i = \frac{(\sum_{AP_j \in VC_i} h_{ij} P_{ot} R_e)^2}{\sigma_{shot}^2 + \sigma_{thermal}^2 + P(AI_i)} \qquad (6)$$
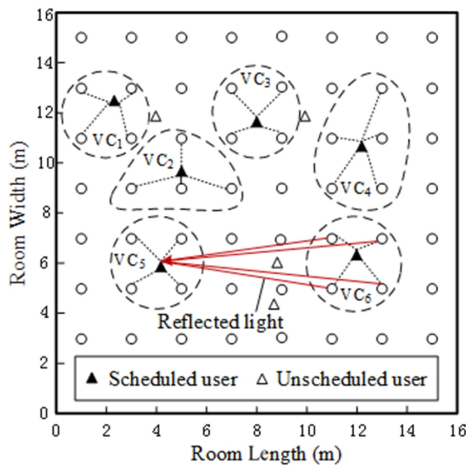

FIG. 3. The AI for the scheduled user in VC_5.

where σ_{shot}^2 and $\sigma_{thermal}^2$ denote the shot noise and thermal noise respectively [12]. h_{ij} is the channel gain between AP j and user i. The $P(AI_i)$ denotes the aggregate interference power received by user i.

From Eq. (6), we see that the interference power caused by AI decreases the user's SINR. Thus the user's average channel rate R will be reduced, influencing the priority factor (i.e. the user's weight p), and changing the scheduling result. In section IV, we give the scheduling result for a time slot by simulation, considering AI and not respectively. In addition, AI decreases the system's sum capacity.

3.3. Proposed Heterogeneous QoS-based Scheduling Scheme

In this part, we introduce effective-bandwidth and effective-capacity theory to guarantee statistical delay QoS in the indoor VLC MUS problem. There is a significant amount of research on various statistical QoS guarantees. Among them, effective-bandwidth theory is an efficient approach that has received extensive research attention in the last decades [15, 16].

Effective bandwidth can be defined as the minimum service rate that a given arrival process can support, to guarantee a QoS requirement specified by a parameter θ. To understand the meaning of this parameter, consider a queuing system with stationary arrival and service processes. Its queue length process $Q(t)$ can be shown to converge in distribution to a random variable $Q(\infty)$, such that

$$-\lim_{X \to \infty} \frac{\log(\Pr\{Q(\infty) > X\})}{X} = \theta \qquad (7)$$

The QoS parameter θ specifies the exponential decay rate of the buffer overflow probability as the buffer threshold X increases to infinity. A larger θ indicates a more stringent QoS requirement, while a smaller one indicates a looser QoS requirement.

The process of data traffic is $\{A(t), t \geq 0\}$, where $A(t)$ is the user's transmission data bits of the process in the interval $[0, t)$. According to effective-bandwidth theory, its log-moment function is given by

$$\Lambda(\theta) = \lim_{t \to \infty} \ln E[\exp(\theta \cdot A(t))]/t, \quad \theta \geq 0 \qquad (8)$$

Thus the corresponding effective bandwidth that meets a certain QoS requirement for user i is

$$EB_i = \Lambda(\theta_i)/\theta_i = \frac{1}{\theta_i} \ln(E[e^{\theta_i A(t)}]) \qquad (9)$$

In this paper, we assume that $\{A(t), t \geq 0\}$ is Poissonian process, i.e. probability distribution function $p_c(A(t) = k) = (\lambda t)^k / k! \cdot e^{-\lambda t}$, $k = 0, 1, 2, \ldots$; thus the effective bandwidth can be expressed as

$$EB_i = \frac{\lambda_i\left(e^{\theta_i} - 1\right)}{\theta_i} \tag{10}$$

where λ_i denotes the average arrival rate, and different traffic has different λ_i.

Based on the PF scheduling mechanism, we introduce effective-bandwidth theory into the priority factor p to guarantee a user's statistical delay QoS in the indoor VLC MUS problem. For each time slot t, the weight of each user is redefined as

$$p_i^{(t)} = r_i^{(t)}\left(\frac{EB_i}{R_i^{(t)}}\right)^{\alpha_i^{(t)}} \tag{11}$$

where $\alpha_i^{(t)}$ is estimated by

$$
\begin{aligned}
\alpha_i^{(t+1)} &= \alpha_i^{(t)} + \Delta\alpha, \quad if\left(\frac{EB_i}{R_i^{(t)}} - \frac{1}{K}\sum_{i=1}^{K}\frac{EB_i}{R_i^{(t)}}\right) > \eta \\
\alpha_i^{(t+1)} &= \alpha_i^{(t)} - \Delta\alpha, \quad if\left(\frac{EB_i}{R_i^{(t)}} - \frac{1}{K}\sum_{i=1}^{K}\frac{EB_i}{R_i^{(t)}}\right) < -\eta
\end{aligned}
\tag{12}
$$

Since it is difficult to achieve the exact necessary effective bandwidth to guarantee the user's QoS requirement, we utilize the updating exponential parameter $\alpha_i^{(t)}$, which tracks the fraction between the user's effective bandwidth and the average rate, i.e $\frac{EB_i}{R_i^{(t)}}$. According to Eq. (12), if the user's average rate is much less than the user's effective bandwidth compared to other users, the exponential parameter $\alpha_i^{(t)}$ is incremented, and the user's scheduling times will be increased. On the contrary, the exponential parameter $\alpha_i^{(t)}$ is decremented, and the user's scheduling times will be decreased. As a consequence, each user's effective bandwidth can be reached, i.e. the QoS requirement is guaranteed.

Thus, our user-centric MUS problem may now be formulated as

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{K} r_i^{(t)}\left(\frac{EB_i}{R_i^{(t)}}\right)^{\alpha_i^{(t)}} \\
s.t. \quad & VC_i \bigcap VC_j = \phi, \quad i,j = 1,\ldots,K, \ i \neq j \\
& \bigcup_{i=1}^{K} VC_i \subset C
\end{aligned}
\tag{13}
$$

Next, we will derive the user's effective capacity for the indoor VLC scheduling problem. According to [17], the effective capacity can be expressed as

$$EC = -\frac{1}{\theta_i}\ln\left(E\left[e^{-\theta_i r_i}\right]\right) \tag{14}$$

By Eq. (14), we can get the effective capacity of user I

$$EC_i = -\frac{1}{\theta_i}\ln\left(\int_0^\infty e^{-\theta_i r_i} p_r(r_i)dr_i\right) \tag{15}$$

where $p_r(r_i)$ is the probability distribution of r_i. In this paper, we define γ_i as the scheduling probability of user i. When user i is not scheduled, $r_i = 0$, and when user i is scheduled, $r_i > 0$. Thus,

$$EC_i = -\frac{1}{\theta_i}\ln\left(e^{-\theta_i(r_i=0)}(1-\gamma_i) + e^{-\theta_i(r_i>0)}(\gamma_i)\right) \tag{16}$$

In the indoor VLC MUS problem, the scheduling probability of user i is given as

$$\gamma_i = \sum_{t=1}^{m}\frac{x_i^{(t)}}{m} \tag{17}$$

where $x_i^{(t)} = 1$ denotes that the user i is scheduled in time slot t, otherwise $x_i^{(t)} = 0$, and m is the total number of time slots. Thus the effective capacity of user i in the indoor VLC MUS problem is

$$
\begin{aligned}
EC_i &= -\frac{1}{\theta_i}\ln\left(e^{-\theta_i(r_i=0)}\left(1 - \sum_{t=1}^{m}\frac{x_i^{(t)}}{m}\right) + e^{-\theta_i(r_i>0)}\left(\sum_{t=1}^{m}\frac{x_i^{(t)}}{m}\right)\right) \\
&= -\frac{1}{\theta_i}\ln\left(1 + \left(e^{-\theta_i(r_i>0)} - 1\right)\left(\sum_{t=1}^{m}\frac{x_i^{(t)}}{m}\right)\right)
\end{aligned}
\tag{18}
$$

IV. SIMULATION RESULTS

In this section we provide some numerical results to demonstrate the proposed heterogeneous QoS-based scheduling scheme, and the impact of AI from Section III. A model 16 m × 16 m × 3 m room is considered, which is covered by a VLC downlink including 8 × 8 uniformly distributed optical APs at a height of 2.5 m. All the APs transmit identical power. Detailed parameters are shown in Table 2. Our simulation results are averaged over 500 independent snapshots, with each snapshot containing 50 time slots.

We evaluate the performance of the user-centric MUS algorithm from the perspective of sum capacity and user fairness. The length of the time window is set to be $T_F = 25$. The sum capacity for one time slot is defined as

$$sum\_capacity = \sum_{i=1}^{K}\log_2\left(1 + \frac{\left(\sum_{AP_j \in VC_i} h_{ij} P_{ot} R_e\right)^2}{\sigma_{shot}^2 + \sigma_{thermal}^2 + P(AI_i)}\right) \tag{19}$$

TABLE 2. Parameters used in the simulation

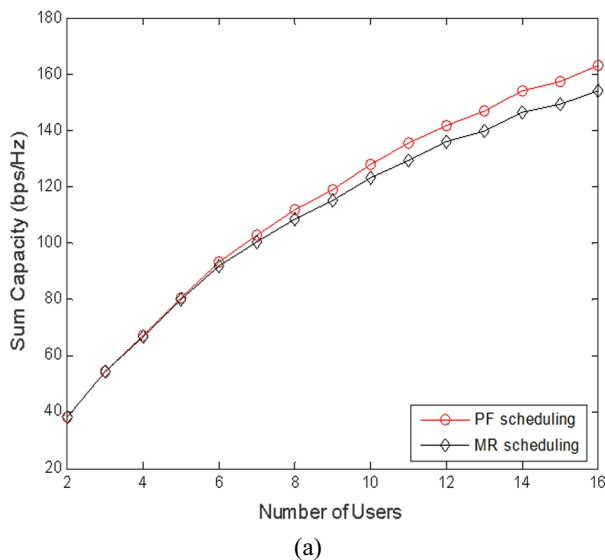| Parameters	Quantity	Value
P_{ot}	Transmitted optical power	20 W
$\Phi_{1/2}$	Semi-angle at half power	70°
B	Bandwidth of the lamp	100 MHz
D_{PA}	Physical area of the PD	1 cm²
$T_s(\psi)$	Gain of the optical filter	1.0
a	Refractive index of the lens at the PD	1.5
R_e	O/E conversion efficiency	0.54 A/W
ψ_F	Half of the receiver's FOV	50°

The values of σ_{shot}^2 and $\sigma_{thermal}^2$ in our simulation have been explicitly given in [12] for the VLC system.

To show the level of fairness experienced by the users, the Service Fairness Index (SFI) of [18] is expressed. The goal of ensuring fairness among users is to guarantee that all users benefit from the same scheduling times within a given period, on the condition that all users have the same QoS requirement. The SFI was defined as [18]

$$SFI = \max_{i,j} |R_i - R_j| / \left(\frac{1}{K} \sum_{l=1}^{K} R_l \right) \qquad (20)$$

where R_i is the average channel rate of user i. From Eq. (20), we can see that the smaller the SFI, the higher the fairness. When there is only one user in the room, that user is always scheduled without competition; we ignore this situation.

Figure 4 shows the system's performance by employing different scheduling schemes after performing the user-centric MUS algorithm, without considering the influence of AI. Each AP is allocated to the user with the highest channel gain in the maximum-rate (MR) scheduling scheme, which achieves the highest sum capacity among scheduling schemes in wireless networks [19]. From Fig. 4, we can see that the PF mechanism is a good scheduling scheme in the user-centric MUS algorithm, showing similar sum capacity to and better fairness performance than the MR mechanism. Therefore, the analysis of AI and our heterogeneous QoS-based scheduling scheme are all based on the user-cenric PF scheduling algorithm. Next, we will give the simulation results when we take account of the AI in the user-centric MUS algorithm.

Figure 5 shows the effect of AI on the scheduling result and performance of the user-centric MUS algorithm. Figure 5(a) shows the scheduling result for time slot 25 without considering the impact of AI, while Fig. 5(b) gives the scheduling result for the same time slot, considering the impact of AI. From Figs. 5(a) and 5(b) we can see that the scheduled users are different, because AI can affect the value of p for each time slot. Moreover, we can see that the sum capacity is reduced, as shown in Fig. 5(c). We thus conclude that AI has a nonnegligible impact on the user-centric MUS problem.

We also evaluate the performance of the proposed heterogeneous QoS-based scheduling scheme. As shown in Appendix II of [20], $EC_i \geq EB_i$ is a sufficient condition for the QoS requirement of Eq. (7) to be satisfied. In our simulations we have fixed $\Delta\alpha = 0.03$, which is a proper value to avoid large variations around the average rate $\eta = 0.01$, which is an appropriate value to guarantee that the user's average rate could reach its effective bandwidth and $\alpha_i^{(0)} = 1$, which is the initial $\alpha_i^{(t)}$. We assume that there are 10 users in the room, classified into two groups, where $\theta_1 = 10^{-6}$ for group 1 and $\theta_2 = 10^{-5}$ for group 2.
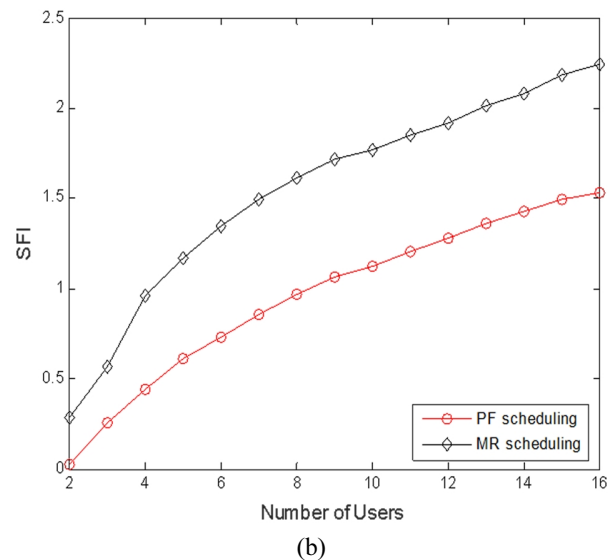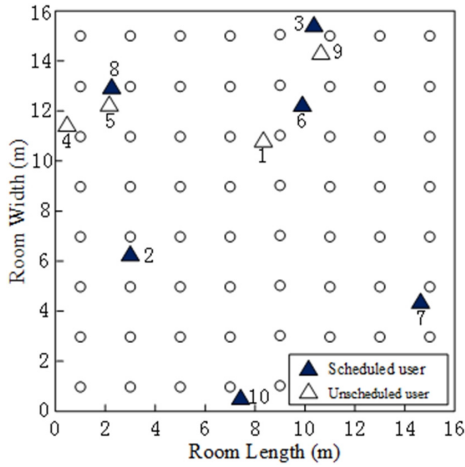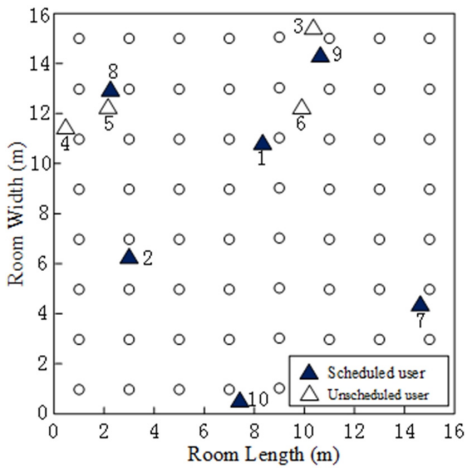

FIG. 4. (a) Sum capacity for different priority factors. (b) SFI for different priority factors.
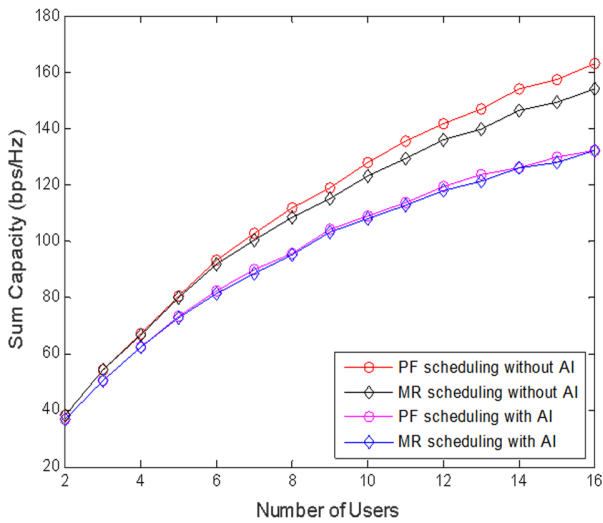
(a)
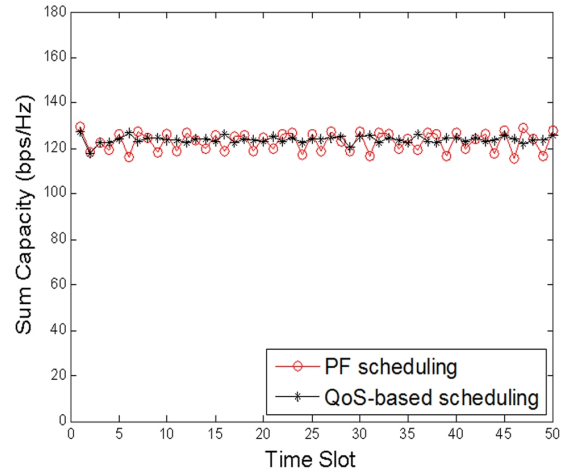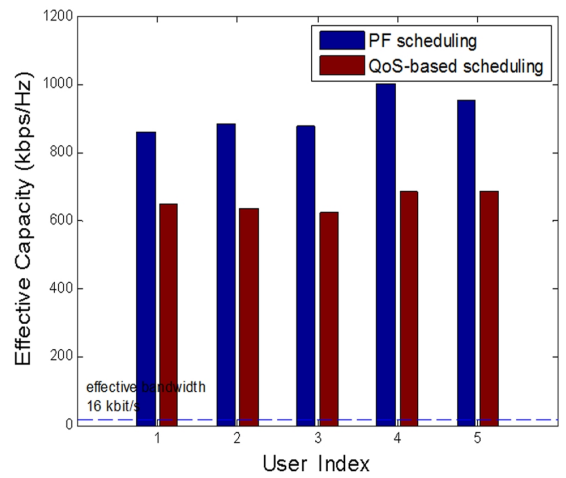

(b)

(c)

FIG. 5. (a) The scheduling result for time slot 25, without AI. (b) The scheduling result for time slot 25, with AI. (c) Sum capacity.
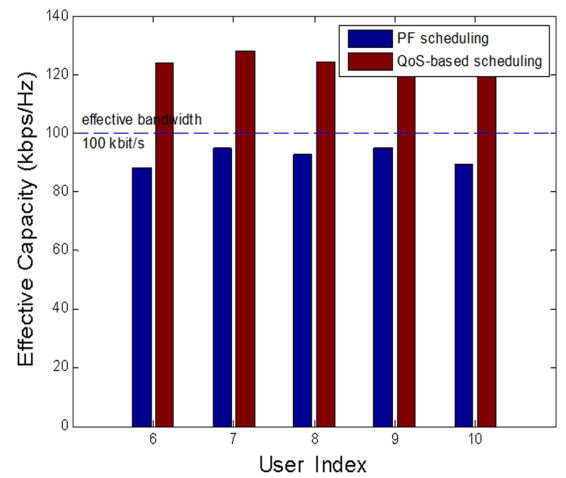

(a)

(b)

(c)

FIG. 6. (a) Sum capacity for different scheduling schemes. (b) Effective capacity for users 1 to 5. (c) Effective capacity for users 6 to 10.

Figure 6 demonstrates the performance of the PF scheme and our proposed heterogeneous QoS-based scheduling scheme

in the user-centric MUS problem. Observed in Fig. 6(a), the sum capacity of our proposed scheme almost equals to that of the PF scheduling scheme. It can be seen from

Fig. 6(b) that when the users of group 1 have a loose QoS requirement, both the PF and our proposed scheduling mechanism can satisfy the user's QoS requirement. However, only our proposed scheduling scheme can guarantee the statistical delay requirement when there is the more stringent QoS requirement of group 2, as shown in Fig. 6(c). Since we introduce the user's effective bandwidth into the PF mechanism, the scheduler selects the user according to the user's current rate, the average rate, and the QoS requirement. Users with larger θ will obtain more scheduling times through the heterogeneous QoS-based scheduling scheme. Therefore, our proposed scheduling scheme can support traffic with a more stringent QoS requirement.

V. CONCLUSION

In this paper, we study the MUS problem for an indoor VLC downlink system. We research the effect of AI on the user-centric MUS problem for the first time. On the basis of the PF scheduling scheme, we creatively introduce effective-bandwidth and effective-capacity theory to the indoor VLC MUS problem for heterogeneous QoS traffic. Simulations show that the AI is a nonnegligible factor in the user-centric MUS problem, and that our proposed heterogeneous QoS-based scheduling scheme can satisfy different users' QoS requirements under the premise of guaranteeing the sum capacity, compared to the existing works.

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