Bandwidth Allocation Under Multi-Level Service Guarantees of Downlink in the VLC-OFDM System

Shuangxing Liu, Xuefen Chi*, and Linlin Zhao

College of Communication Engineering, Jilin University, 5372, Nanhu Road, Changchun 130012, P. R. China

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In this paper, we explore a low-complex bandwidth allocation (BA) scheme with multi-level service guarantees in VLC-OFDM systems. Effective capacity theory, which evaluates wireless channel capacity from a novel view, is utilized to model the system capacity under delay QoS constraints of the link layer. Since intensity modulation of light is used in the system, problems caused by frequency selectivity can be neglected. Then, the BA problem can be formulated as an integer programming problem and it is further relaxed and transformed into a concave one. Lagrangian formulation is used to reformulate the concave problem. Considering the inefficiency of traditional gradient-based schemes and the demand for distributed implementation in local area networks, we localize the global parameters and propose a quasi-distributed quadratic allocation algorithm to provide two-level service guarantees, the first level is QoS oriented, and the second level is QoE oriented. Simulations have shown the efficient performance of the proposed algorithm. The users with more stringent QoS requirements require more subcarriers to guarantee their statistical delay QoS requirements. We also analyze the effect of subcarrier granularity on the aggregate effective capacity via simulations.

Keywords: Bandwidth allocation, VLC, OFDM, Effective capacity, Multi-level service guarantee

OCIS codes: (060.2605) Free-space optical communication; (060.4080) Modulation; (060.4510) Optical communications; (060.4256) Networks, network optimization

I. INTRODUCTION

The next generation communication networks are required to support high data rate services while guaranteeing multi-level quality of service (QoS) metrics, such as delay, value of service and a certain level of quality of experience (QoE) which is a widely used metric reflecting the users' satisfaction with the multimedia service. Due to the shortage of radio spectrum, traditional radio communication systems suffer from limited channel capacity. Compared to the radio-based wireless communication, visible light communication (VLC) brings multiple advantages such as greater bandwidth, higher data rate, being harmless to human bodies, ubiquitous data transmission and so on [1-3]. Orthogonal frequency division multiplexing (OFDM) which allows for parallel transmission on orthogonal subcarriers with a low-complexity transceiver [4] was introduced into VLC to improve data rate, mitigate the fading effects resulting from delay spread, and avoid low-frequency ambient interference [5]. In VLC-OFDM systems, the amplitude variation of the OFDM signal drives the intensity change of LED light. Once LED works in the non-linear region, the OFDM signal would be distorted. In this paper, we assume that LEDs are always working in their linear region. Because of the feature of weak penetration through obstacles and the short distance of data transmission, VLC is usually applied in indoor local area networks.

Most of the previous works about VLC-OFDM systems focused on the implementation and improvement of optical OFDM. Only a few works put their effort on the effective resource allocation algorithms. The authors in [6] have investigated the performance of a single carrier-frequency division multiple access (SC-FDMA) VLC system in the...
downlink of a multi-user data transmission system, and they jointly optimized the total transmission power and the subcarriers allocation for the VLC access point. The authors in [7] have analyzed the nonlinear clipping distortion of an asymmetrically clipped optical OFDM based VLC system and proposed an optimal power allocation method for reducing the clipping distortion. The authors in [8] have reported a novel asynchronous multiple access using a flexible bandwidth allocation scheme in the VLC system with 32/64QAM-OFDM, adopting quadrature amplitude modulation OFDM modulation. However, most previous works about resource allocation in VLC-OFDM systems neglected the delay in QoS demand of services.

In wireless networks, with the growing proliferation of delay-sensitive traffic, it is obligatory to support a wide variety of communication services with diverse delay QoS requirements. Nevertheless, it is tough to provide deterministic delay QoS guarantees in a wireless network because the wireless channel is varying all the time. The concept of statistical delay QoS in effective capacity theory has captured increasing attention of researchers. Effective capacity presents a novel perspective on the capacity of channels in terms of link-layer delay-QoS metric [9], which describes the supported maximum constant arrival rate of the system subject to the statistical delay-QoS constraint for a given service process.

In the study of radio frequency (RF) wireless communication systems with OFDM modulation, researchers have introduced the concept of statistical delay guarantees into their research [10]. The authors in [9] have developed an optimal strategy to maximize the throughput of the relay-based multiuser OFDMA systems with respect to the joint subchannel assignment and power control under both delay-QoS guarantees and average power constraints. The authors in [11] have proposed a delay QoS provision algorithm, which evolved an effective capacity model to capture the effect of channel fading on the queuing behavior of the link in wireless OFDM networks. The authors in [12] have investigated the resource allocation scheme for the uplink of the LTE network under statistical delay QoS guarantees. However, the previous works about resource allocation under statistical delay guarantees in RF-OFDM systems adopted the centralized scheme and required a coordinator with powerful functionality, which conflicts with the low-complexity design idea of coordinator in local area networks. Additionally, for the unipolar nature of VLC-OFDM signals, OFDM technique used in RF systems can’t be applied in VLC systems directly.

We notice that the researchers in [13, 14] have the similar perspective with us in terms of statistical delay QoS guarantees in VLC systems. The authors in [13] have investigated the resource allocation algorithm under delay QoS constraints for heterogeneous visible-light and RF femtocell. The authors in [14] have proposed a novel QoS-driven non carrier sensing random access mechanism for the multi-packet reception-capable VLC system. However, we are different, we cope with the difficulties of discrete bandwidth allocation arising from the OFDM implemented in the VLC system and consider the specific problems of the optical channel. Furthermore, we try to support multi-level service guarantees in a simple way.

In this paper, we focus on the bandwidth allocation (BA) problem under the constraints of minimum bit rate, the maximum bandwidth usage efficiency and delay QoS guarantees in downlink of an indoor VLC-OFDM system. We propose a quasi-distributed BA scheme to provide multi-level service guarantees.

In OFDM system, bandwidth of the system is discretized as a bunch of subcarrier blocks (SBs). Intensity of light is modulated in the system, so the problem caused by frequency selectivity can be neglected. Therefore, the difference of VLC channel gain among SBs that are allocated to a user can be ignored. The BA problem can be formulated as an integer programming problem to decide the number of SBs allocated to each user with the target of maximizing the aggregate effective capacity. To solve the problem, we relax the integer constraints and reformulate the problem as a continuous optimization problem, where the optimum variables are defined as ratio factors indicating the percentage of bandwidth allocated to users. It’s mathematically proved that the relaxed problem is concave with respect to ratio factors, which can be solved by convex optimization techniques.

Although gradient-based approaches have been proposed to solve the convex optimization problem, these schemes show many defects [12] such as oscillatory behavior, sensitivity to choice of initial values, etc. In our research, we target to support heterogeneous statistical delay QoS constraints, which inevitably aggravate the oscillatory behavior of gradient-based techniques. In addition, the conflict between guaranteeing minimum bit rate and maximizing bandwidth usage efficiency reduces the convergence rate of gradient-based schemes. Furthermore, the gradient-based approaches require high computational capability. It is essential to explore a simple and efficient BA algorithm. In this paper, we propose a quasi-distributed quadratic allocation scheme to lighten the burden of the coordinator by localizing the global parameters. We propose to provide multi-level service guarantees, we blend the statistical delay QoS guarantee with probability bandwidth request in the algorithm, the first one is QoS oriented, the second one is QoE oriented. We aim to create a space where an application can be tailored.

SB granularity refers to the size of a subcarrier in VLC-OFDM systems. In this paper, we also analyze the relationship between the bandwidth utilization and SB granularity via simulations.

The rest of the paper is organized as follows. In Section II, we describe the system model and channel model, and derive the expression of effective capacity of the VLC-OFDM system. The formulation of the BA problem is described in Section III. In Section IV, we propose a quasi-distributed BA scheme. The numerical and simulation results are shown in Section V. Finally, we make a conclusion in Section VI. The notations used in this paper are summarized in Table 1.
Table 1. The main symbol notation

| Symbol | Description |
|--------|-------------|
| $l$    | Order of Lambertian emission |
| $\phi_{1/2}$ | Semi-angle at half power |
| $A$    | Physical area of the photo-detector (PD) |
| $T_s$  | Gain of the optical filter |
| $\psi_{ir}$ | Angle of irradiation |
| $\psi_{in}$ | Angle of incidence |
| $g(\psi_{in})$ | Gain of an optical concentrator |
| $n$    | Refractive index |
| $\Psi_c$ | Width of the field of view (FOV) |
| $\rho$ | Reflectance factor |
| $\omega_1$ | Angle of irradiance to a reflective point |
| $\omega_2$ | Angle of irradiance to a receiver |
| $q$    | Electronic charge |
| $\tau$ | Detector’s responsivity |
| $B_e$ | Equivalent noise bandwidth |
| $I_{bg}$ | Background current |
| $r$    | Boltzmann’s constant |
| $G$    | Open-loop voltage gain |
| $\eta$ | Fixed capacitance of the PD per unit area |
| $\Gamma$ | FET channel noise factor |
| $\delta_n$ | FET transconductance |
| $I_1$  | Noise bandwidth factor |
| $I_2$  | Noise bandwidth factor |
| $T_k$  | Absolute temperature |
| $B$    | Available bandwidth |
| $R_k$  | Bit-rate constraint of user $k$ |
| $p$    | Block probability |
| $L$    | Total number of RBs |
| $P_t$  | Transmitted power |

II. SYSTEM MODEL

In this paper, we consider the downlink of the VLC-OFDM system, as shown in Fig. 1. We focus on the resource allocation problem and consider that $K$ users are distributed in the room. The users are indexed by $K = \{1, \ldots, k, \ldots, K\}$. We consider heterogeneous delay QoS requirements that are characterized by a vector $\theta = [\theta_k]_{K \times 1}$ with the element $\theta_k$ denoting the QoS exponent in effective capacity theory of the user $k$, $k \in K$.

We assume that all users are stationary while there are moving obstructions in the room, such as human beings, which might block the LOS links of downlinks. The OFDM technique is utilized in the downlink transmission of the VLC system [3] to achieve parallel communications. The available bandwidth $B$ is divided into $L$ SBs with equivalent bandwidth [3]. The SBs are indexed by the set $L = \{1, \ldots, l, \ldots, L\}$. SB granularity $\varpi$, which is referred as the size of an SB, is the basic unit while allocating bandwidth. An IM/DD (intensity modulation/direct detection) technique is used in the system, which implies that the phase information is lost and only the intensity of LED light is modulated with data. Therefore, the transmitted signal must be positive real, and at least half of the SBs must be used to realize the Hermitian conjugate of the complex-valued symbol after modulation. Consequently, at most half of the bandwidth can be exploited for signal transmission [15].

2.1. Channel Model

In the VLC system, signals are detected by a photodetector (PD) at the receiver. The received signals are a mix of direct portion with single/multiple reflected portion [18]. The direct portion is called the line-of-sight (LOS) signal, which provides high channel gain but is vulnerable to interruption. Otherwise, the non-line-of-sight (NLOS) signal, which has lower channel gain but is robust to environmental change. In this paper we will consider both LOS signal and NLOS signals on the first reflection [13, 16, 17].

In an optical LOS channel, as shown in Fig. 2, the direct current (DC) gain is given as [13]:

$$H(0) = \frac{(La + 1)AT_k}{2\pi D_r} \cos i_1(\psi_{ir}) g(\psi_{in}) \cos(\psi_{in}), \quad \text{if } \psi_{in} \leq \psi_c,$$

$$0, \quad \text{if } \psi_{in} > \psi_c,$$

where $A$ is the physical area in a PD, $D_r$ is the distance between a transmitter and a receiver, $\psi_{ir}$ is the angle of
irradiation of the LED lights, $\psi_{in}$ is the angle of incidence, $\psi_c$ denotes the width of the field of view (FOV) at the receiver, $T_s$ is the gain of the optical filter used, and $La$ is the order of Lambertian emission which is given by the semi-angle $\phi_{1/2}$ at half illumination of an LED as [17]:

$$La = \frac{\ln 2}{\ln \cos \phi_{1/2}}$$

$g(\psi_{m})$ denotes the gain of an optical concentrator [18] [19]:

$$g(\psi_{m}) = \begin{cases} 
\frac{La^2}{\sin^2 \psi_c}, & \text{if } \psi_{in} \leq \psi_c \\
0, & \text{if } \psi_{in} > \psi_c
\end{cases}$$

The VLC LOS channel might be blocked by obstructions. The blocking event is represented by a random variable $\kappa$, $\kappa = 1$ if the LOS channel is blocked, otherwise $\kappa = 0$. We assume that $\kappa$ obeys the Bernoulli distribution [13]. The LOS channel is blocked with probability $p_k$ which is decided by the communication scenario and the location of user $k$. The probability mass function of $\kappa$ for user $k$ is expressed as:

$$f_k(\kappa) = \begin{cases} 
 p_k, & \text{if } \kappa = 1 \\
 1 - p_k, & \text{if } \kappa = 0
\end{cases}$$

The received optical power is given by the DC gain on the LOS path $H(0)$ and the first reflected paths $H_{ref}(0)$, which may be written as [17]:

$$p_r = p_t H(0) + \int_{wall} p_t dH_{ref}(0)$$

$P_t$ and $P_r$ denote the transmitted and received power respectively. The channel DC gain of the first reflection is characterized by [17]:

$$dH_{ref}(0) = \begin{cases} 
(\ell+1)AT_{ref} \frac{J \cos \psi_c g(\psi_{m}) \cos(\psi_{in}) dA_{walls}}{2\pi D_1^2 D_2^2}, & \text{if } \psi_{in} \leq \psi_c \\
0, & \text{if } \psi_{in} > \psi_c
\end{cases}$$

where $D_1$ denotes the distance between the user and a reflecting surface, $D_2$ denotes the distance between the reflective point and the receiver, $\rho$ is the reflectance factor, whilst $dA_{walls}$ is a small reflective area, and $J = \cos(\psi_1) \cos(\psi_2)$, where $\psi_1$ and $\psi_2$ denote the angle of irradiance to a reflective point and the angle of irradiance to the receiver respectively. The first reflective channel model is shown in Fig. 3.

We consider both shot noise and thermal noise [13, 17]. Hence, the Gaussian noise has a total variance of $\sigma^2$, which is the sum of shot noise and thermal noise:

$$\sigma^2 = \sigma^2_{shot} + \sigma^2_{thermal}$$

The variance of shot noise $\sigma^2_{shot}$ is given by [18]:

$$\sigma^2_{shot} = 2q\tau P_s B_e + 2qI_{bg} I B_e$$

where $q$ is the electronic charge, $\tau$ is the detector’s responsivity, $B_e$ is the equivalent noise bandwidth, $I_{bg}$ is the background current caused by the background light. The variance of thermal noise is given by [17]:

$$\sigma^2_{thermal} = \frac{8\pi r T_k}{G} \eta AI B_e^2 + \frac{16\pi^2 r T_k \Gamma}{g_m} \eta^2 A I^2 B_e$$

where $r$ is the Boltzmann’s constant, $T_k$ is the absolute temperature, $G$ is the open-loop voltage gain, $\eta$ is the fixed capacitance of the PD per unit area, $\Gamma$ is the FET channel noise factor, and finally, $g_m$ is the FET transconductance. The noise bandwidth factors $I_1$ and $I_2$ are constant experimental values.

The SNR at the receiver for user $k$ on SB $l$, where $k \in K$, $l \in L_k$ is denoted by $\gamma_{k,l}$:

$$\gamma_{k,l} = \frac{\left(\tau P_{ref}^k\right)^2}{\sigma^2_{k,l}}$$

According to the Shannon capacity equation, the upper bound of the achievable data rate for user $k$ on the SB $l$ is given by:
\[ R_{k,j} = \bar{\sigma} \log_2(1 + \gamma_{k,j}) \]

where \( \bar{\sigma} = \frac{B}{L} \) is SB granularity. As discussed above, at most half of the bandwidth can be exploited for signal transmission, we can get the upper bound of the achievable data rate for user \( k \), which can be expressed as:

\[ R_k = \sum_{i=1}^{L} z_{k,i} \frac{\bar{\sigma}}{2} \log_2(1 + \gamma_{k,i}) \]

where \( z_{k,i} \in \{0,1\} \), \( z_{k,i} = 1 \) if user \( k \) occupies SB \( i \), otherwise \( z_{k,i} = 0 \).

Since an IM/DD technique is utilized, there is no explicit carrier of a single frequency but the intensity of light is modulated [3]. In this respect, the problem caused by frequency selectivity can be neglected. In addition, the VLC channel is modeled as a two-rate channel in which the DC gain is modulated [3]. In this respect, the problem caused by frequency selectivity can be neglected. Therefore, there is no difference of channel DC gain among SBs allocated to a user. We assume that \( L_k \) SBs are allocated to user \( k \), and for any SB \( i \) allocated to user \( k \), we have \( \gamma_{k,i} = \gamma_{k,i} \). The achievable data rate for user \( k \) can be rewritten as:

\[ R_k = L_k \frac{\bar{\sigma}}{2} \log_2(1 + \gamma_k) \]  \hspace{1cm} (1)

### 2.2. Effective Capacity of VLC

Effective capacity theory, which was proposed by Wu and Negi in 2003 [20], is the dual problem of effective bandwidth. It characterizes the maximum constant arrival rate of a given service process under the statistical delay QoS constraint. The QoS exponent \( \theta \) describes the steady state delay violation probability, the expression is shown as \( P_T(d > d^* \} = e^{-\theta d^*} \), where \( d \) is the steady state delay, \( d^* \) is the delay bound, and \( \theta \) is determined by the arrival and service processes [21]. It should be noted that a smaller \( \theta \) indicates a looser QoS constraint whereas a larger \( \theta \) implies a more stringent QoS constraint.

The effective capacity [12, 20] for user \( k \) is given by:

\[ C_k(\theta_k, \bar{\sigma}; z_{k,j}) = -\frac{1}{\theta_k} \ln E(e^{-\theta_k \gamma_k}) \]  \hspace{1cm} (2)

The instantaneous data rate can be expressed as [13]:

\[ R_k = \begin{cases} \Re_{1,k}, & \text{with probability } 1 - p_k \\ \Re_{2,k}, & \text{with probability } p_k \end{cases} \]

where \( \Re_{1,k} \) and \( \Re_{2,k} \) denote the achievable transmission rate for user \( k \) with and without VLC LOS reception, respectively. Therefore, the effective capacity for user \( k \) is given by:

\[ C_k(\theta_k, \bar{\sigma}; z_{j,k}) = \begin{cases} \frac{1}{\theta_k} \ln(1 - p_k e^{-\theta_k \gamma_k} + p_k e^{\theta_k \gamma_k}), & \text{if } \psi_m \leq \psi_k \\ 0, & \text{if } \psi_m > \psi_k \end{cases} \]  \hspace{1cm} (3)

### III. PROBLEM FORMULATION

The bandwidth allocation problem is formulated as the maximization of aggregate effective capacity, which can be expressed as:

\[ \max_k C_k(\theta_k, \bar{\sigma}; L) \]  \hspace{1cm} (Problem 1)

s.t. \( \begin{align*} C_k(\theta_k, L_k) &\geq R_k \quad k \in K \\ 1^T L &= L \end{align*} \)

The objective of the optimization Problem 1 is to find a SBs allocation strategy to maximize the aggregate effective capacity under specific statistical delay constraints. \( L = [L_k]_{K \times 1} \), \( k \in K \) is the SBs indicated matrix which satisfies \( 1^T L = L \). The aggregate effective capacity of the VLC system, defined as \( C_k(\theta_k, \bar{\sigma}; z) \), is given by:

\[ C_k(\theta_k, \bar{\sigma}; z) = \sum_{k=1}^{K} C_k(\theta_k, \bar{\sigma}; z_{j,k}) \]  \hspace{1cm} (4)

Physically, constraint (a) guarantees the minimum bit-rate requirement for user \( k \). Constraint (b) physically ensures the maximum bandwidth utilization.

Problem 1 is an integer non-linear programming problem. A solution to solve an integer programming problem is to relax the integer constraint. Certainly, Problem 2 is not actually solved by the relaxation of the integer constraint. However, it has been shown in [22] that solving the dual of the relaxed problem provides solutions that are arbitrarily close to the original, non-relaxed problem [13].

\( L_k \) denotes the bandwidth allocated to user \( k \), it is a continuous variable in the interval \([0, L]\). Let \( \beta_k = L_k/L \), where \( k \in K \), \( \beta_k \) is the ratio factor for user \( k \) which is a continuous variable in the interval \([0, 1]\). The achievable data rate for user \( k \) is rewritten as:

\[ R_k = \beta_k \frac{\bar{\sigma} L}{2} \log_2(1 + \gamma_k) \]

Next, let \( R_{k,1} = \frac{\beta_k}{2} \bar{\sigma} L \log_2(1 + \gamma_{k,1}) \), \( R_{k,2} = \frac{\beta_k}{2} \bar{\sigma} L \log_2(1 + \gamma_{k,2}) \),
where $\gamma_{k,i}$ and $\gamma'_{k,i}$ denote the SNRs for user $k$ with and
without LOS reception, respectively. So the effective capacity for user $k$
given by (3) can be expressed as:

$$C_k^e(\theta,\sigma;\beta_k) = \frac{1}{\theta} \ln \left(1 - p_i e^{-\theta R_k^e} + p_e e^{-\theta R_i^e}\right), \text{ if } \psi_n \leq \psi_c,$$

$$\text{if } \psi_n > \psi_c$$

(5)

Then, the relaxed optimization problem of Problem 2 could be reformulated as follows:

$$\max_{\beta} C_k(\theta,\sigma;\beta) \quad \text{(Problem 2)}$$

s.t. (a) $C_k^e(\theta,\beta_k) \geq R_k^e \quad \forall k \in K$

(b) $\sum_{k=1}^{K} \beta_k = 1 \quad \forall k \in K$

(c) $0 \leq \beta_k \leq 1 \quad \forall k \in K$

where $\beta = [\beta_k]_{k=1}^{K}$ denotes the SBs allocation matrix. Constraint (b) involves the sum of $\beta_k$, it is a global constraint to ensure the maximum bandwidth usage efficiency. Constraint (a) is a local constraint that guarantees the minimum bit rate requirement for each user.

Lemma 1: Problem 2 is a concave optimization problem.

Proof: See Appendix A.

IV. A QUASI-DISTRIBUTED ALGORITHM

Problem 2 may be solved with the aid of centralized tools which require a coordinator with powerful functionality, which runs contrary to the low-complexity design idea of coordinator in local area networks. It may be appropriate to apply distributed tools to find the solution. Nevertheless, it is difficult to achieve completely distributed algorithms. Traditional gradient-based algorithms show many defects such as oscillatory behavior, sensitivity to choice of initial values, etc. In our research, we aim to support heterogeneous statistical delay QoS constraints which inevitably aggravate the oscillatory behavior of gradient-based techniques. Moreover, the conflict between guaranteeing minimum bit rate and maximizing bandwidth utilization reduces the convergence rate of gradient-based schemes. It is essential to explore a simple and efficient BA algorithm. In this section, we propose a quasi-distributed quadratic BA algorithm, the first one is QoS oriented, and the second one is QoE oriented.

As discussed in Section III, Problem 2 is a concave one which implies that we can use Lagrangian formulation to reformulate the optimization problem [22]. The Lagrangian function of Problem 2 with constraints (a)-(c) is expressed as:

$$L(\theta,\sigma;\lambda,\mu) = C_k(\theta,\sigma;\beta) - \lambda \left(\sum_{k=1}^{K} \beta_k - 1\right) - \mu_k (R_k^e - C_k^e)$$

where $\lambda \geq 0$ and $\mu_k \geq 0$, $k \in K$, are the Lagrange multipliers. We define $\lambda$ as the global multiplier and $\mu_k$ as the local multiplier. The objective function in Problem 2 can be written as:

$$C_k(\theta,\sigma;\beta) = \min_{\lambda,\mu} L(\theta,\sigma;\lambda,\mu)$$

The maximum of $C_k(0,\beta)$ can be expressed as:

$$\max_{\beta} C_k(0,\sigma;\beta) = \max_{\lambda,\mu} \min_{\beta} L(0,\sigma;\lambda,\mu)$$

(6)

According to Karush-Kuhn-Tucker (KKT) conditions, when the following two conditions is satisfied:

$$\lambda = 0 \text{ or } \sum_{k=1}^{K} \beta_k - 1 = 0$$

$$\mu_k = 0 \text{ or } R_k^e - C_k^e = 0, \forall k \in K$$

(7)

(8)

we have the following equations:

$$\max_{\beta} C_k(0,\sigma;\beta) = \max_{\lambda,\mu} \min_{\beta} L(0,\sigma;\lambda,\mu)$$

$$= \min_{\lambda,\mu} \max_{\beta} L(0,\sigma;\lambda,\mu)$$

which implies that the optimal SBs allocation matrix $\beta^*$ can be obtained by solving:

$$\min_{\lambda,\mu} \max_{\beta} L(0,\sigma;\lambda,\mu)$$

(9)

The dual objective function $g(\lambda,\mu)$ is defined as the maximum value of the Lagrangian function over $\beta$, which can be expressed as:

$$g(\theta,\sigma;\lambda,\mu) = \max_{\beta} L(\theta,\sigma;\beta,\lambda,\mu)$$

Eq. (9) can be expressed as the minimum of $g(\lambda,\mu)$ which is described as:

$$\min_{\lambda,\mu} g(\theta,\sigma;\lambda,\mu)$$

sub $\lambda \geq 0, \mu \geq 0$

(10)

Eq. (10) is always a convex optimization problem. There is a duality gap between the optimal primal objective expressed in Problem 2 and its optimal dual objective Eq. (10), which is always nonnegative [13]. According to the central result in convex analysis that the duality gap reduces to zero at the optimum, when the problem is convex [22, 23]. Therefore, the primal problem can be equivalently solved
The feasible region of Eq. (10), we take $\lambda$ and $\mu$ as constants, and obtain the optimal $\beta^*$, which can be written as:

$$\beta^* = \arg \max_{\beta \in \mathbb{R}^K} L(0, \sigma; \beta, \lambda, \mu)$$

The second derivative of $L(\beta, \lambda, \mu)$ with respect to $\beta_k$, $k \in \mathbb{K}$, is expressed as:

$$\frac{\partial^2 L(\beta, \lambda, \mu)}{\partial \beta_k^2} = C_k \beta^* + u_k C_k^*$$

As discussed in Appendix A, we have $C_k \beta^* \leq 0$, and $\mu_k$ is greater than zero, we have $\frac{\partial^2 L(\beta, \lambda, \mu)}{\partial \beta_k^2} \leq 0$, which implies that $L(\beta, \lambda, \mu)$ is concave with respect to $\beta_k$. The optimal $\beta_k^*$ may be achieved by solving [7]:

$$\frac{\partial L(\beta, \lambda, \mu)}{\partial \beta_k} = C_k^* - \lambda + \mu_k C_k^* = 0$$

Next, we utilize $\beta_k^*$ to update $\lambda$ and $\mu$. To achieve distributed implementation, we localize the global multiplier $\lambda$ into local parameters.

According to (11), we have:

$$C_k^* = \frac{\bar{\lambda}}{1 + \mu_k}$$

Observe from Eq. (12), the optimal $\beta_k^*$ is a function of $\frac{\bar{\lambda}}{1 + \mu_k}$. Instead of updating $\lambda$ and $\mu$ respectively, which contributes to a slow convergence rate, we update $\frac{\bar{\lambda}}{1 + \mu_k}$ directly. We let $A_k = \frac{\bar{\lambda}}{1 + \mu_k}$. According to Appendix B, the feasible region of $A_k$ is $\left\{ \frac{p_k R_{1,k} + \xi (1 - p_k) R_{1,k}}{p_k + \xi (1 - p_k)} \mid p_k R_{2,k} + (1 - p_k) R_{2,k} \right\}$, where $\xi = e^{\theta (R_{1,k} - R_{2,k})}$. We assume that $0 < p < 1$, the closed-form of $\beta_k^*$ can be described as:

$$\beta_k^* = \frac{1}{-\theta_k (R_{1,k} - R_{2,k})} \ln \frac{p_k (A_k - R_{2,k})}{(1 - p_k) (R_{1,k} - A_k)}$$

The proof of Eq. (13) can be seen in Appendix B. Based on Eq. (13), we can adjust the bandwidth allocated to user $k$ through changing the value of $A_k$.

To find the optimal $A_k$, we firstly take $A_k$ as constants, and get the corresponding optimal $\beta_k^*$. Then we use $\beta_k^*$ to update $A_k$ after that we use the newly $A_k$ to obtain the newly $\beta_k^*$. This process continues until $\beta_k^*$ converges or reaches the maximum iterations. $A_k$ is updated according to:

$$A_k(t + 1) = A_k(t) + \text{Step}_k(t) \left( 1 - \sum_{i=1}^{K} \beta_i^* \right)$$

where $\text{Step}_k(t)$ is the iterative step function, the value of which is not smaller than zero. $f_k \left( 1 - \sum_{i=1}^{K} \beta_i^* \right)$ is the iterative direction function which determines to increase or decrease $A_k$, and it takes the value of -1, 0, or 1.

Next, we investigate the iterative step function which guarantees the convergence of $A_k$ after finite iterations. The iterative step is described as:

$$\text{step}_k(t) = \begin{cases} \text{step}_k(t) + \Delta t, & \text{if } f_k(t) = f_k(t_i) \\ \text{step}_k(t) - \Delta t, & \text{if } f_k(t) \neq f_k(t_i) \\ \text{step}_k(t_i), & \text{if } f_k(t) = 0 \end{cases}$$

where $f_k(t)$ is the iteration direction of the $t$th iteration for user $k$. $\Delta t$ and $\Delta t'$ are the increments of iteration step which are not smaller than zero. $f_k(t_i)$ is the last iteration direction when $f_k(t_i)$ is not equal to zero. The optimal solution is sensitive to the initial value of $\text{step}_k(t)$. In this paper, we let:

$$\text{step}_{k,ini} = \frac{p_k R_{1,k} + \xi (1 - p_k) R_{1,k}}{p_k + \xi (1 - p_k)} - A_{k,ini}$$

Then, we explore the iterative direction function. To achieve the maximum bandwidth efficiency, the sum of $\beta_k^*$ should be close to one. According to Appendix B, $\beta_k^*$ is monotonic decreasing with $A_k$. After the current iteration, if the sum of $\beta_k^*$ is less than one, there would be extra bandwidth that remained in the system. And all users can still attempt to increase their ratio factors by decreasing $A_k$ in the next iteration. On the contrary, if the sum of $\beta_k^*$ is greater than one after the current iteration, all users would have to decrease their ratio factors by increasing $A_k$. The iteration direction function for user $k$ can be described as:

$$\begin{cases} -1 & \text{with probability } \alpha_k \\ 0 & \text{with probability } (1 - \alpha_k) \end{cases}$$

$$f_k \left( 1 - \sum_{i=1}^{K} \beta_i^* \right) = \begin{cases} 1 & \text{if } 0 \leq 1 - \sum_{i=1}^{K} \beta_i^* < \sigma, \\ 0 & \text{if } 1 - \sum_{i=1}^{K} \beta_i^* = 0 \end{cases}$$

where $\alpha_k$ is the iteration direction probability for user $k$. According to Appendix B, $\beta_k^*$ is monotonic decreasing with $A_k$. After the current iteration, if the sum of $\beta_k^*$ is less than one, there would be extra bandwidth that remained in the system. And all users can still attempt to increase their ratio factors by decreasing $A_k$ in the next iteration. On the contrary, if the sum of $\beta_k^*$ is greater than one after the current iteration, all users would have to decrease their ratio factors by increasing $A_k$. The iteration direction function for user $k$ can be described as:

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$$f_k \left( 1 - \sum_{i=1}^{K} \beta_i^* \right) = \begin{cases} 1 & \text{if } 0 \leq 1 - \sum_{i=1}^{K} \beta_i^* < \sigma, \\ 0 & \text{if } 1 - \sum_{i=1}^{K} \beta_i^* = 0 \end{cases}$$
Eq. (16) illustrates that the ratio factors would not be changed anymore when less than one SB is remained to be allocated in the system. \( \alpha_k \) is the bandwidth request probability for user \( k \) which reflects user’s QoE requirements. The introduction of \( \alpha_k \) into the algorithm provides a space for multi-level service guarantees.

The BA algorithm is a quadratic allocation one. The first one is QoS oriented. We allocate bandwidth to each user to guarantee their minimum bit rate requirement. \( A_k \) is initialized to the value of guaranteeing the minimum bit rate requirement of user \( k \). For each user \( k \), we let \( C_k^r(\beta_k) = R_k \). We can obtain the minimum ratio factor \( \beta_{k,ini} \) through the binary search method. \( \beta_{k,ini} \) indicates the minimum bandwidth for user \( k \) to guarantee their minimum bit rate requirement. Based on Eq. (13), we can get \( A_{k,ini} \). \( A_{k,ini} \) is also the upper bound to ensure minimum bit rate requirement. The second one is QoE oriented. We allocate the remainder bandwidth to users based on their bandwidth request probability. A bigger bandwidth request probability for user \( k \) implies a larger probability to allocate more bandwidth to use \( k \).

Figure 4 illustrates how the algorithm works. We assume that \( \alpha_k \) is equal to one. After the \( t \)th iteration, \( A_k \) changes from \( A_{k,t-1} \) to \( A_{k,t} \), the iterative direction \( f(t) = -1 \), the iterative step is \( \text{step}(t) \). In the \((t+1)\)th iteration, if \( f(t) \neq f(t+1) \) which means that the optimal \( A_k \) falls into region 1, we obtain the \((t+1)\)th iterative step according to expression Eq. (15).

We assume that after the \((t+1)\)th iteration, \( A_k \) changes from \( A_{k,t} \) to \( A_{k,t+1} \), as shown in Fig. 4. Next, we compare the value of \( f(t+2) \) and \( f(t+1) \). If \( f(t+2) \) is not equal to \( f(t+1) \), the optimal \( A_k \) falls into region 2, if \( f(t+2) \) is equal to \( f(t+1) \), the optimal \( A_k \) falls into region 3. Each iteration makes \( A_k \) get closer to the optimal solution.

Based on the above discussions, the quasi-distributed BA scheme is constituted by an iterative algorithm which searches for the optimal ratio factors based on the update of \( A_k \). \( A_k \) is initialized to a feasible value \( A_{k,ini} \), the optimal ratio factors are calculated based on Eq. (13) at the user side. Then, coordinator calculates the value of \( 1 - \sum_{k=1}^{K} \beta_k \) and broadcasts the calculated result to each user. After that, each user obtains its iterative direction function based on Eq. (16). Next, users calculate its iterative step function according to Eq. (15) based on the new value of iterative direction function, and then update \( A_k \) according to Eq. (14). This process continues until convergence. The quasi-distributed BA scheme is formally described in Table 2.

After obtaining the optimal ratio factors, we discretize the bandwidth allocated to each user into the integral multiple of SB granularity. Firstly, based on \( \beta_k^* \) and \( L_k \), we obtain \( L_k \). And then we discretize \( L_k \) through the equation:

\[
L_k = \left\lfloor \frac{L_k}{\beta_k^*} \right\rfloor \log_2(1 + \gamma_k)
\]

where \( L_k^* \) is the number of SBs allocated to user \( k \), \( \beta_k \in \mathbb{K} \). Operator \( \lfloor \cdot \rfloor \) is the rounding down operator, and operator \( \lceil \cdot \rceil \) is the rounding up operator. The achievable data rate for user \( k \) after discretization is given by:

\[
R_k = L_k^* \frac{\sigma}{2} \log_2(1 + \gamma_k)
\]

TABLE 2. The quasi-distributed BA scheme

| Input | 
|-------|
| \( \theta_k \): Delay requirement of each user \( k \), \( k = 1, 2, \ldots, K \) |
| \( R_k \): Rate requirement of each user \( k \), \( k = 1, 2, \ldots, K \) |
| \( p_k \): Blocking probability of each user \( k \), \( k = 1, 2, \ldots, K \) |
| \( \alpha_k \): Bandwidth request probability of each user \( k \), \( k = 1, 2, \ldots, K \) |

| Initialization | |
|---------------|
| \( t = 1 \) |
| for each user |
| \( A_k(1) = A_{k,ini} \) |
| End for |

| While \( t \) dose not reach its maximum |
| Get optimal \( \beta_k \) |
| For each user \( k \) |
| User \( k \) solve the problem presented in Eq. (13) |
| End for |

| If sum(\( \beta_k \)) < \( \Theta \) |
| Break; |
| End if |

| Update \( A_k \) |
| For each user \( k \) |
| Iterative direction is updated according to Eq. (16); |
| Iterative step is updated according to Eq. (15); |
| \( A_k \) is updated according to Eq. (14); |
| End for |
| \( t = t + 1 \) |
| End while |
| For each user \( k \) |
| \( L_k^* = \left\lfloor \frac{L_k}{\beta_k^*} \right\rfloor \) |
| End for |

| Output L |
According to (4), (5) and (18), we obtain the aggregate effective capacity.

V. NUMERICAL AND SIMULATION RESULTS

Our simulation model is based on the downlink transmissions of a multi-user VLC-OFDM system, shown in Fig. 1. The two-rate transmission channel model is used. We assume that 10 terminals which are divided into three groups are uniformly distributed in the room, the users in the same group experience the same delay QoS requirements while the users in different groups experience heterogeneous delay QoS requirements. The main system parameters are given in Table 3.

Figure 5 demonstrates the convergence behavior of the quasi-distributed BA scheme in different blocking situations where the VLC blocking probabilities are 0.1, 0.2 and 0.5 respectively. We assume that all users experience the same QoE requirement, and for any \( k \in K \), we let \( a_k \) be equal to 0.8. As shown in Fig. 5, the BA algorithm which indeed finds the ratio factors converges to the optimal value within 20 iterations.

Figure 6 illustrates the effect of the delay exponent \( \theta \) on the aggregate effective capacity. We compare the performance between the proposed BA scheme and the average bandwidth allocation scheme when the blocking probabilities are 0.2 and 0.5, respectively. We assume that all users experience the same delay exponents, and the same QoE requirement. For any \( k \in K \), we let \( a_k \) be equal to 0.8. Observed from Fig. 6, the BA scheme can reach a greater aggregate effective capacity than the average bandwidth allocation scheme does, and the advantages of the BA scheme would be greater as the QoS requirement becomes more stringent. In addition, the aggregate effective capacity is reduced upon increasing the delay exponent \( \theta \), the VLC system is sensitive to the delay constraints, and the total effective capacity degrades rapidly for \( \theta \geq 0.1 \).

Figure 7 demonstrates the ratio factors versus the user index at a 0.2 VLC blocking probability, in conjunction

![Fig. 5. The aggregate effective capacity values versus the total number of iterations.](image)

![Fig. 6. The aggregate effective capacity versus the statistical delay exponent.](image)
Bandwidth Allocation Under Multi-Level Service Guarantees of Downlink in the…”

with \( \theta = 0.001 \) for users in group 1, \( \theta = 0.01 \) for users in group 2 and \( \theta = 0.1 \) for users in group 3. We assume that all users experience the same QoE requirement, and for any \( k \in K \), we let \( \alpha_k \) be equal to 0.8. Observed from Fig. 7, almost the same number of SBs are allocated to the users with the same delay exponents. The slight difference among different users in the same group is mainly caused by the different positions. Furthermore, more SBs are assigned to the users with larger delay exponent \( \theta \), which implies a more stringent QoS requirement, to guarantee their delay QoS constraint. Figure 8 shows the numbers of SBs allocated to each user.

Figure 9 demonstrates the effect of bandwidth request probability \( \alpha \) of the users in group 3 on the effective capacity. We assume that \( \theta = 0.001 \) for users in group 1, \( \theta = 0.01 \) for users in group 2 and \( \theta = 0.1 \) for users in group 3. And the users in group 1 and group 2 experience the same QoE requirement. For any user \( k \) in group 1 and group 2, we let \( \alpha_k = 0.6 \). Additionally, the VLC blocking probability is 0.2. Observed from Fig. 9, since a greater bandwidth request probability for user \( k \) implies higher probability to allocate SBs to user \( k \), with increasing the bandwidth request probability of group 3 the effective capacity of group 3 is raised. However, because the system bandwidth is fixed, the bandwidth allocated to the users in group 1 and group 2 decrease, so the aggregate effective capacity of group 1 and group 2 decreases. Additionally, the aggregate effective capacity of group 1, group 2 and group 3 remains almost the same as the bandwidth request probability of group 3 increases. It implies that the bandwidth request probability just affects the distribution of SBs, but has no effect on the aggregate effective capacity of the system. Moreover, as shown in Fig. 9, even if the bandwidth request probability of the users in group 3 is zero, there still are SBs allocated to the users in group 3. This is because the proposed algorithm primarily allocates bandwidth to users to satisfy their minimum bit rate requirements.

Figure 10 shows the effect of SB granularity on the aggregate effective capacity before and after discretization of \( L_k \) in the situation that the VLC blocking probabilities are 0.2 and 0.5, respectively. We assume that all users experience the same delay exponents, the system bandwidth \( B \) is 20 MHz. And all users have the same bandwidth request probability, for any \( k \in K \), we let \( \alpha_k \) be equal to 0.8. As Fig. 10 shows, the aggregate effective capacity
after discretization decreases as SB granularity increases, and it approaches the aggregate effective capacity before discretization when the SB granularity is smaller than \( B/2^p \) kHz. In fact, the gap between the aggregate effective capacity before and after discretization is affected by the discretization precision of \( L_k \) which is determined by SB granularity. A smaller SB granularity implies a higher discretization precision, which contributes to a smaller gap. Additionally, a smaller gap indicates smaller reduction of bandwidth utilization, as shown in Fig. 10, a smaller SB granularity implies smaller reduction of bandwidth utilization.

VI. CONCLUSION

In this paper, we have investigated the BA problem in the downlink of a VLC-OFDM system under multi-level service guarantees. Effective capacity theory is used to characterize the system capacity. Since an IM/DD technique is utilized in the system, the difference between SBs allocated to a user can be ignored. Therefore, the BA problem can be formulated as an integer programming problem. We relax the integer condition and have proved mathematically that the relaxed problem is a concave one. Lagrangian formulation is used to reformulate the concave problem. Considering the inefficiency of the traditional gradient-based schemes and the demand for distributed implementation in local area networks, we localized the global parameters and propose a quasi-distributed algorithm which is a quadratic allocation scheme, the first one is QoS oriented, and the second one is QoE oriented. Our simulation demonstrates that the quasi-distributed scheme can converge to the suboptimal solution within small epochs. By comparing with the average bandwidth allocation scheme, the BA scheme can achieve a greater aggregate effective capacity, and the advantages are getting greater as the QoS requirements are getting more stringent. The VLC system is sensitive to the delay constraints, and the aggregate effective capacity degrades rapidly for \( \theta \geq 0.1 \). More SBs are assigned to the users with larger delay constraints, and it approaches the aggregate effective capacity before discretization. The VLC link for terminal \( k \) is given by:

\[
\frac{\partial^2 C_k^i(\beta_k)}{\partial \beta_k^2} = \frac{p_k (1 - p_k) \theta_k (R_{1,k} - R_{2,k})^2 e^{-\theta_k R_{1,k} + R_{2,k}}}{(1 - p_k) e^{-\theta_k R_{1,k}} + p_k e^{-\theta_k R_{2,k}}}.
\]

Since \( \beta_k \rightarrow 0, 0 \leq p \leq 1 \), we get \( \frac{\partial^2 C_k^i(\beta_k)}{\partial \beta_k^2} \leq 0 \). As a result, the objective function of Problem 2 is a concave function with respect to \( \beta_k \).

APPENDIX A

The first derivative of the effective capacity \( C^i_k \) from the VLC link for terminal \( k \) is given by:

\[
\frac{\partial C^i_k(\beta_k)}{\partial \beta_k} = \frac{(1 - p_k) R_{1,k} e^{-\theta_k R_{1,k}} + p_k R_{2,k} e^{-\theta_k R_{2,k}}}{(1 - p_k) e^{-\theta_k R_{1,k}} + p_k e^{-\theta_k R_{2,k}}}.
\]

The second derivative of the effective capacity \( C^i_k \) from the VLC link for terminal \( k \) is given by:

\[
\frac{\partial^2 C_k^i(\beta_k)}{\partial \beta_k^2} = \frac{p_k (1 - p_k) \theta_k (R_{1,k} - R_{2,k})^2 e^{-\theta_k R_{1,k} + R_{2,k}}}{(1 - p_k) e^{-\theta_k R_{1,k}} + p_k e^{-\theta_k R_{2,k}}}.
\]

APPENDIX B

The first derivative of the effective capacity \( C^i_k \) respect to the variable \( \beta_k \) is:

\[
\frac{\partial C_k^i(\beta_k)}{\partial \beta_k} = \frac{(1 - p_k) R_{1,k} e^{-\theta_k R_{1,k}} + p_k R_{2,k} e^{-\theta_k R_{2,k}}}{(1 - p_k) e^{-\theta_k R_{1,k}} + p_k e^{-\theta_k R_{2,k}}}
\]

Substituting (19) into (12), we can get:

\[
(1 - p_k) R_{1,k} e^{-\theta_k R_{1,k}} + p_k R_{2,k} e^{-\theta_k R_{2,k}} = A_k ((1 - p_k) e^{-\theta_k R_{1,k}} + p_k e^{-\theta_k R_{2,k}})
\]

(20)

Since \( e^{-\theta_k R_{1,k}} > 0 \), (20) can be converted into:

\[
(1 - p_k) (R_{1,k} - A_k) e^{-\theta_k (R_{1,k} - R_{2,k})} = p_k (A_k - R_{2,k})
\]

We assume that \( 0 < p < 1 \), when \( R_{1,k} < A_k < R_{2,k} \), we can get the closed-form of the optimal solution \( \beta_k \) :

\[
\beta_k = \frac{1}{-\theta_k (R_{1,k} - R_{2,k})} \ln p_k (A_k - R_{2,k})\frac{1}{(1 - p_k) (R_{1,k} - A_k)}
\]

Additionally, the first derivative of \( \beta_k^* \) with respect to \( A_k \) can be expressed as:

\[
\frac{\partial \beta_k^*}{\partial A_k} = \frac{1}{-\theta_k (A_k - R_{2,k}) (R_{1,k} - A_k)}
\]

where \( R_{1,k} < A_k < R_{2,k} \) and \( \theta > 0 \), we get \( \frac{\partial \beta_k^*}{\partial A_k} < 0 \) which implies that \( \beta_k^* \) is monotonic decreasing with \( A_k \). Since \( 0 \leq \beta_k^* \leq 1 \), the feasible region of \( A_k \) is expressed as:
\[
A_k \in \left[ \frac{p_k R_{k,1} + \xi (1 - p_k) R_{k,1}}{p_k + \xi (1 - p_k)}, p_k R_{k,1} + (1 - p_k) R_{k,1} \right]
\]
where \( \xi = e^{-\theta (R_{k,1} - R_{k,2})} \).

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