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On relay selection and power allocation in cooperative free-space optical networks

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Abstract Drawing increasing attention, free-space optics (FSO) is a cost-effective technology to support data intensive communications. Cooperative diversity is considered to be an effective means for combating weather turbulence in FSO networks. In this paper, we consider the challenging problem of joint relay selection and power allocation in FSO networks. The objective was to maximize the FSO network-wide throughput under constraints of a given power budget and a limited number of FSO transceivers. The problem is formulated as a mixed integer nonlinear programming (MINLP) problem, which is NP-hard. We first adopt the reformulation-linearization technique (RLT) to derive an upper bound for the original MINLP problem. Due to the relaxation, the solutions obtained from RLT are infeasible. We then propose both centralized and distributed algorithms using bipartite matching and convex optimization to obtain highly competitive solutions. The proposed algorithms are shown to outperform the noncooperative scheme and an existing relay selection protocol with considerable gains through simulations.

Keywords FSO · Cooperative diversity · Convex optimization · Power allocation · Reformulation-linearization technique · Weather turbulence

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1 Introduction

Drawing increasing attention, free-space optics (FSO) is a cost-effective technology with applications ranging from high-capacity military communications to "last-mile" broadband access solutions [24,25]. Recently, the US National Aeronautics and Space Administration (NASA) successfully demonstrated a high-definition (HD) video transmission from the International Space Station 260 miles away from the Earth using the Optical Payload for Lasercomm Science (OPALS) system [26], while FSO is also shown effective to enhance the scalability of wireless mesh networks [24]. Although FSO links are able to support data intensive communications, a line-of-sight (LOS) path is required and there are many factors leading to significant link performance degradation. Most common is the adverse atmospheric conditions (e.g., due to the temperature and pressure changes or flying objects), which can greatly degrade the link-level performance. Fading mitigation techniques have to be employed to maintain a good performance for FSO system [27].

To this end, topology control in FSO networks has been studied and proved to be effective to achieve strong connectivity and robust FSO networks [23–25]. On the other hand, spatial diversity techniques, which are extensively studied in conventional RF communication systems [22], have recently been introduced to FSO networks. Furthermore, multiple-input multiple-output (MIMO) FSO systems can achieve significant diversity gain under the presence of atmospheric fading by deploying multiple transmit or receiver apertures [9,12]. Under the circumstance of a limited number of transceivers or antennas, another cost-effective alternative (compared to MIMO-FSO) is to exploit the cooperative diversity, which is studied in this paper.

Cooperative diversity is considered as an effective means for combating weather turbulence in FSO networks [1–3].

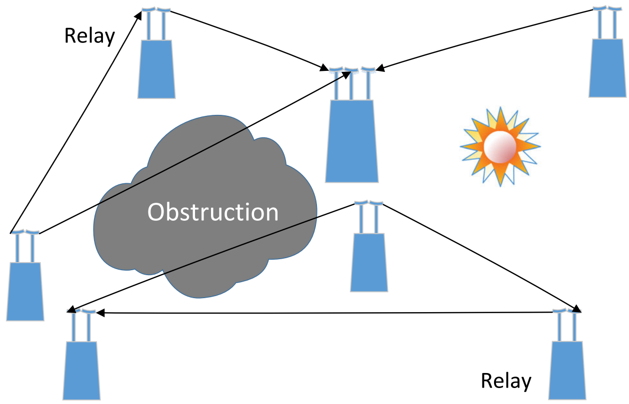

Fig. 1 Illustration of a cooperative FSO network

Usually, FSO networks are well planned with perfect LOS paths. However, under the situations of severe weather or flying objects, an FSO base station may still experience degraded communication performance. However, if the FSO base station (BS) transmits cooperatively through another FSO BS, which serves as a relay and whose surrounding weather condition is relatively better, the link quality degradation can be greatly mitigated. In [3], one-relay cooperative diversity is demonstrated to achieve significant gains over noncooperative FSO links that suffer from correlated fading. The authors in [18] also show that multihop relaying can be employed in FSO networks.

In this paper, we consider the decode-and-forward (DF) cooperation strategy and use one relay for FSO links [15]. The cooperative FSO network framework is illustrated in Fig. 1, within which each FSO BS is equipped with a small number, e.g., two or three, of transceivers. During operation, the LOS path might be influenced by severe weather conditions, but the cooperative FSO transmission strategy will use the relay to mitigate the weather influence and enhance the system performance. We consider one-relay cooperative FSO communications with intensity modulation and direct detection (IM/DD). In the proposed cooperative FSO network, a BS can transmit directly to the destination BS or use another BS as relay. In the latter case, the source BS first transmits symbols to the relay BS in one time slot. Then, the source and relay BSs will simultaneously transmit the symbols to the destination BS in the next time slot.

Unlike the prior work on cooperative FSO networks that focused on physical layer aspects, we investigate the problem of maximizing the network-wide throughput with consideration of power budget and cost (i.e., the number of available FSO transceivers) constraints. Specifically, we formulate the problem of joint relay selection and power allocation as a mixed integer nonlinear programming (MINLP) problem. A reformulation-linearization technique (RLT) is first utilized to derive an upper bound for the original MINLP problem [21]. However, due to the relaxation, the solution obtained by the RLT scheme is infeasible.

We then develop both centralized and distributed algorithms to solve the formulated problem. First, we design a centralized algorithm for relay selection based on *maximum weight matching* on a bipartite graph. We then show that the remaining power allocation problem is convex and then solve it using the *gradient method*, a widely used convex optimization approach. In the case when centralized coordination is not available, we develop a distributed algorithm that uses only local channel state information (CSI). The distributed algorithm is based on the *Distributed Extended Gale-Shapley* (DiEGS) algorithm originally designed for solving the *stable marriage problem* [7]. The performance of the proposed algorithms is evaluated with simulations. The proposed algorithms outperform a noncooperative scheme and an existing relay selection scheme with considerable gains.

The remainder of this paper is organized as follows. The related work is discussed in Sect. 2. We introduce the system model in Sect. 3. We then present the problem formulation and a RLT method to obtain a upper bound in Sect. 4. The centralized and distributed algorithms are developed to address the MINLP problem in Sect. 5. Our simulation studies are presented and discussed in Sect. 6. Section 7 concludes this paper.

2 Related work

FSO has attracted significant interest both in academia and in industry as a promising solution for high-capacity, long-range communications [28]. Weather turbulence strongly affects FSO communication links. How to overcome such effects is the focus of many related works. In [20], the authors introduced a multipath fading resistant FSO communication system architecture to combat adverse weather conditions. The influence of turbulence-accentuated interchannel crosstalk on wavelength division multiplexing (WDM) FSO system performance has been discussed in [4,29].

The cooperative diversity has been exploited in FSO networks in several recent papers [1–3]. Relay-assisted FSO communications have been studied in [8,13,19]. Both serial and parallel relaying coupled with amplify-and-forward and decode-and-forward cooperation modes were addressed in [19]. The authors adopted multiple-relay communications to shorten the distance between FSO BSs and reduce hop counts, resulting in considerable performance improvements. The work in [19] was extended in [13], and the authors further provided an interesting diversity gain analysis. In [8], the authors proposed to select only a single relay in each transmission slot, to avoid the need for synchronizing multiple relays' transmissions.

In a recent work [3], a one-relay cooperative diversity scheme was proposed for combating turbulence-induced fading and cooperative diversity was analyzed for noncoherent FSO communications. Numerical results demonstrated considerable performance gains over noncooperative FSO networks. Abou-Rjeily and Haddad in [2] studied cooperative FSO systems with multiple relays. An optimal power allocation strategy was proposed to enhance diversity order and minimize error probability. It turned out that the solution was to transmit with the entire power along the strongest link between the source and destination.

The prior works on optimal relay selection or relay placement in FSO networks were mainly focused on maximizing the diversity gain, reducing the outage probability, or maximizing the capacity for an individual BS. In this paper, we consider the challenging problem of relay selection and power allocation under power and cost constraints, aiming to maximize the overall FSO network capacity. We develop effective algorithms that are based on bipartite matching and convex optimization to compute highly competitive solutions to maximize the total throughput of the cooperative FSO network.

3 System model

Cooperative communications are investigated in this paper as a fading mitigation method for FSO networks. When the direct link between source and destination suffers from atmospheric turbulence, FSO BSs can use relays to enhance link quality.

3.1 Channel model

FSO links are highly directional and are prone to degradation caused by weather turbulence. In this paper, we consider both effects of path loss and turbulence-induced fading over FSO links [18]. The optical channel state h is a product of two factors, as

$$h = h_l \cdot h_f, \tag{1}$$

where h_l denotes the propagation loss and h_f represents the impact of atmospheric turbulence. h_l is a function of optical wavelength λ and link length d, as [27]

$$h_l = \frac{A_{\mathrm{TX}} \cdot A_{\mathrm{RX}} \cdot e^{-\alpha d}}{(\lambda \cdot d)^2}, \tag{2}$$

where A_{TX} and A_{RX} are aperture areas of the transmitter and receiver, respectively. The coefficient α is a parameter related to wavelength and environment. For h_f, we assume the impact of atmospheric turbulence can be modeled as log-normal fading, which is a widely used model in the FSO literature, especially under weak-to-moderate turbulence conditions.

The FSO channel model can be written as

$$y = h \cdot x + n, \tag{3}$$

where x and y are the transmitted and received signals, respectively; n is the additive Gaussian noise. With the non-cooperative strategy, the maximum achievable data rate for a communication pair is given by the Shannon formula as

$$w_{s,d} = B \log_2 \left(1 + \frac{|h_{s,d}|^2 P_s}{\sigma^2}\right), \tag{4}$$

in which $h_{s,d}$ denotes the channel state of the direct link between source and destination, P_s is the transmit power, and σ^2 is the noise power. Let $W_{s,r}$ denote the maximum achievable capacity between source and destination when one relay is used, which can be expressed as

$$\begin{aligned} w_{s,r} = \frac{B}{2} \min \Bigg\{ & \log_2 \left(1 + \frac{|h_{s,r}|^2 P_s}{\sigma^2}\right), \\ & \log_2 \left(1 + \frac{|h_{s,d}|^2 P_s}{\sigma^2} + \frac{|h_{r,d}|^2 P_r}{\sigma^2}\right) \Bigg\}, \end{aligned} \tag{5}$$

where P_s and P_r represent the source and relay's transmit power, and $h_{s,r}$ and $h_{r,d}$ are the channel states of the source-relay link and the relay-destination link, respectively.

3.2 Cooperation model

We consider a relay-assisted IM/DD FSO communication system with the decode-and-forward strategy [10]. The transmission takes two time slots. In the first time slot, the source station first transmits symbols to one relay station, which will detect the information symbols; in the second time slot, the source and relay will simultaneously transmit the symbols to the destination.

The cooperation model consists of K BSs. Each BS may transmit directly or use one relay to assist its transmission. We assume the base stations will not decline a cooperation request under any circumstance (i.e., the BSs are truly cooperative). We have M, $(M \leq K)$, BSs generating traffic (termed source BSs) to be sent to other BSs (termed destination BSs). The set of source BSs is denoted by $\mathscr{S}$, and the set of destination base stations is denoted by $\mathscr{D}$. The cardinalities of $\mathscr{S}$ and $\mathscr{D}$ are both M, since in the general case, any BS can have traffic to be sent to any other BS. The destination BS of source BS S_i is denoted as D_i. Usually, an FSO BS has a limited number of transceivers, which limits the number of communication links that a BS can have simultaneously.

For every source–destination pair, we assume at most one relay is assigned. Assuming CSI is known, every source would like to greedily choose its best relay to maximize its data rate. Furthermore, every BS has a limited number of transceivers and a limited power budget. In this paper, we thus focus on the problem of relay selection and transmit power allocation to maximize the overall capacity of the cooperative FSO network.

4 Problem formulation and upper bound

In this section, the problem of joint relay selection and power allocation is formulated as an MINLP problem. An RLT-based method is also introduced so that a upper bound on the network-wide throughput can be obtained [21].

4.1 Problem formulation

First, we define the following set of index variables to indicate relay selection.

$$I_{i,j} = \begin{cases} 1, & \text{if BS } i \text{ selects BS } j \text{ as relay} \\ 0, & \text{otherwise,} \end{cases} \quad \text{for all i, j } \in \{1, 2, \cdots, M\}. \tag{6}$$

Note that $I_{i,i} = 1$ indicates that BS i transmits directly to its destination BS without using any relay.

The limited number of transceivers at the BSs is translated into constraint

$$\sum_{i=1}^{M} I_{i,j} \leq T_j, \ \text{for all } j \in \{1, 2, \cdots, M\}, \tag{7}$$

where T_j is the number of transceivers at BS j. The BSs will use their transceivers to cooperate with each other and allocate power to each transceiver.

The power budget constraint for each base station is represented as

$$\sum_{j=1}^{M} P_{i,j} \leq \bar{P}_i, \ \text{for all } i \in \{1, 2, \cdots, M\}, \tag{8}$$

where $P_{i,j}$ is the power that BS i allocates to assist source j and $\bar{P}_i$ is the power budget of BS i.

In FSO communications, eye safety issues should always been considered. For eye safety considerations, we enforce a peak power bound for the transmit powers, as

$$P_{i,j} \leq P_{\max}, \ \text{for all } i, j \in \{1, 2, \cdots, M\}. \tag{9}$$

We assume that during data transmission, the allocated powers do not change in each time slot.

Given the transceivers and power constraints, the objective is to develop a relay selection and power allocation scheme for each BS, while the overall network capacity is maximized. The problem is formulated as follows.

$$\max \sum_{i=1}^{M} \left(I_{i,i} \cdot w_{s,d}^{i,i} + \sum_{j=1, j\neq i, j\neq D_i}^{K} I_{i,j} \cdot w_{s,r}^{i,j} \right) \tag{10}$$

$$s.t. \ \sum_{i=1}^{M} I_{i,j} \leq T_j, \ \text{for all } j \in \{1, 2, \cdots, M\} \tag{11}$$

$$\sum_{j=1}^{K} I_{i,j} \leq 1, \ \text{for all } i \in \{1, 2, \cdots, M\} \tag{12}$$

$$\sum_{j=1}^{M} P_{i,j} \leq \bar{P}_i, \ \text{for all } i \in \{1, 2, \cdots, M\} \tag{13}$$

$$0 \leq P_{i,j} \leq P_{\max}, \ \text{for all } i, j \in \{1, 2, \cdots, M\} \tag{14}$$

$$I_{i,j} \in \{0, 1\}, \ \text{for all } i, j \in \{1, 2, \cdots, M\}, \tag{15}$$

where the capacity achieved by direct communication (i.e., $w_{s,d}^{i,i}$) and the capacity achieved by using BS j as relay (i.e., $w_{s,r}^{i,j}$) can be calculated using (4) and (5), respectively. Each source can choose to either transmit directly or use one relay, which is specified in constraint (12).

4.2 Upper bound

The formulated problem is an MINLP problem, which is NP-hard in general. We first adopt the RLT method to relax the MINLP problem to obtain a upper bound. RLT is a relaxation technique that can be used to produce a tight polyhedral outer approximation or a linear programming (LP) relaxation for a nonlinear, nonconvex polynomial programming problem [21]. It has been used in our prior work to address various complex optimization problems [11,14].

The first step of relaxation is to allow the binary I-variables to take real values in [0, 1]. The second step is to linearize the logarithmic terms in the objective function. We have $w_{s,d}^{i,i}$ as a logarithmic function of $P_{i,i}$, as

$$w_{s,d}^{i,i} = B \log_2 \left(1 + \frac{|h_{i,i}|^2 P_{i,i}}{\sigma^2} \right), \tag{16}$$

where $h_{i,i}$ is the channel gain from source BS i to its destination BS. We linearize this logarithmic relationship in (16) over some tightly bounded interval using the polyhedral outer approximation [21]. Letting $P_{i,i}$ be 0 and $P_{\max}$, we obtain the lower and upper bounds of the term inside the log function, which are denoted, respectively, as

$$\underline{\eta}_i = 0 \ \text{ and } \ \overline{\eta}_i = 1 + \frac{|h_{i,i}|^2 P_{\max}}{\sigma^2}. \tag{17}$$

We then use the four-point approximation and obtain the following new linear constraints.

$$\begin{cases} w_{s,d}^{i,i} \geq \frac{\log_2 \overline{\eta}_i - \log_2 \underline{\eta}_i}{\overline{\eta}_i - \underline{\eta}_i} (\eta_i - \underline{\eta}_i) + \log_2 \underline{\eta}_i \\ w_{s,d}^{i,i} \leq \frac{\eta_i - \eta_k}{\eta_k \ln 2} + \log_2 \eta_k, \end{cases} \tag{18}$$

where $\eta_k = \underline{\eta}_i + \frac{k(\overline{\eta}_i - \underline{\eta}_i)}{3}$, for $k = 0, 1, 2, 3$.

Next, we replace the product term $I_{i,i} \cdot w_{s,d}^{i,i}$ with a substitution variable $v^i = I_{i,i} \cdot w_{s,d}^{i,i}$. Since $I_{i,i}$ and $w_{s,d}^{i,i}$ are each bounded by their respective lower and upper bounds, we obtain the following RLT bound-factor product constraints [21].

$$\begin{cases} (I_{i,i} - 0) \cdot \left(w_{s,d}^{i,i} - \log_2 \underline{\eta}_i\right) \geq 0 \\ (I_{i,i} - 0) \cdot \left(\log_2 \overline{\eta}_i - w_{s,d}^{i,i}\right) \geq 0 \\ (1 - I_{i,i}) \cdot \left(w_{s,d}^{i,i} - \log_2 \underline{\eta}_i\right) \geq 0 \\ (1 - I_{i,i}) \cdot \left(\log_2 \overline{\eta}_i - w_{s,d}^{i,i}\right) \geq 0. \end{cases} \tag{19}$$

Therefore, substituting $I_{i,i} \cdot w_{s,d}^{i,i}$ with v^i, we obtain four linear constraints for variable v^i, and the product term is removed from the objective function. We deal with the terms $I_{i,j} \cdot w_{s,r}^{i,j}$ in the same manner.

The capacity achieved by relaying is more complicated, which can be computed as

$$w_{s,r}^{i,j} = \frac{B}{2} \min \left\{ \log_2 \left(1 + \frac{|h_{i,j}|^2 P_{i,i}}{\sigma^2}\right), \log_2 \left(1 + \frac{|h_{i,i}|^2 P_{i,i}}{\sigma^2} + \frac{|h_{j,i}|^2 P_{j,i}}{\sigma^2}\right) \right\}, \tag{20}$$

where $h_{j,i}$ is actually h_{j,D_i}, which represents the channel condition between the relay BS and the destination BS. We introduce new variables $w_{s,r,1}^{i,j}$, $w_{s,r,2}^{i,j}$, and $t_{i,j}$ to have

$$\begin{cases} w_{s,r,1}^{i,j} = \frac{B}{2} \log_2 \left(1 + \frac{|h_{i,j}|^2 P_{i,i}}{\sigma^2}\right) \geq t_{i,j} \\ w_{s,r,2}^{i,j} = \frac{B}{2} \log_2 \left(1 + \frac{|h_{i,i}|^2 P_{i,i}}{\sigma^2} + \frac{|h_{j,i}|^2 P_{j,i}}{\sigma^2}\right) \geq t_{i,j}. \end{cases} \tag{21}$$

Now, maximizing $w_{s,r}^{i,j}$ is equivalent to maximizing $t_{i,j}$. We then linearize the first logarithmic relationship using the polyhedral outer approximation as discussed earlier in this section. The second logarithmic relationship can be linearized similarly, but we need to introduce an additional variable

$$\xi_{i,j} = \frac{|h_{i,i}|^2 P_{i,i}}{\sigma^2} + \frac{|h_{j,i}|^2 P_{j,i}}{\sigma^2}, \tag{22}$$

which is bounded. The logarithmic relationship

$$w_{s,r,2}^{i,j} = \frac{B}{2} \log_2 \left(1 + \xi_{i,j}\right), \tag{23}$$

can be linearized with the polyhedral outer approximation.

Finally, we replace the product term $I_{i,j} \cdot t_{i,j}$ with a substitution variable $v^{i,j}$. Since $I_{i,j}$ and $t_{i,j}$ are both bounded, we obtain the RLT bound-factor product constraints for $v^{i,j}$ in the same way as in (19).

Now, the original MINLP problem is relaxed to a LP problem with the additional constraints and substitution variables, which can be solved in polynomial time with an LP solver. Unfortunately, the solution obtained from LP is usually infeasible due to the relaxations made, but the solution can be used as an upper bound for the original problem. To obtain a feasible solution, a local search algorithm is needed to find a feasible solution in the neighborhood of the RLT solution [11,14]. We omit this part for brevity in this paper.

5 Solution algorithms

In this section, we develop centralized and distributed relay selection and power control algorithms to solve the formulated problem with near-optimal solutions.

5.1 Centralized algorithm

The formulated problem is an MINLP problem with binary variables $I_{i,j}$'s and real variables $P_{i,j}$'s, which is NP-hard [11]. We develop a centralized algorithm that first determines the relay selections and then allocates transmit powers to selected relays. The main idea is to fix I-variables first and then consider optimized power allocation at each relay.

The first phase of the centralized algorithm is to solve the relay selection problem. The relay selection problem here can be interpreted as a weighted bipartite matching problem, which can be solved with polynomial-time algorithms such as *Hungarian algorithm* [5]. We construct a bipartite graph as follows: one disjoint set consists of the source BSs $\mathscr{S}$, and the other disjoint set contains the destination BSs $\mathscr{D}$ and the BSs that have available transceivers to relay traffic for the sources. We call such a BS a *relay BS*, and the set of relay BSs is denoted by $\mathscr{R}$. The weight of each matching edge is the corresponding link capacity. Such matching problem can be solved with polynomial-time algorithms, such as Hungarian algorithm [5].

The relay selection algorithm is presented in Algorithm 1, which incorporates maximum weight matching. Let N_j be the number of sources that relay j serves. Initially, N_j is set to be as large as possible to accommodate more sources; however, the power that each source is allocated may be too small to achieve the desired capacity gain in this case. As the algorithm evolves over time, N_j will be decreased finally to one. If a source i cannot achieve the desired capacity gain even with one relay that is allocated with all the power budget $\bar{P}_i$, it has to transmit directly to its destination. Actually, for every source i and relay j, we can calculate the minimum

Algorithm 1: Centralized Relay Selection Algorithm

1 Initialize source set $\mathscr{S}$, relay set $\mathscr{R}$ and destination set $\mathscr{D}$;
2 Remove source $\{i|h_{i,j} < h_{i,i}, \forall j\}$ from $\mathscr{S}$ and set $I_i = 1$;
3 **while** *$\mathscr{S}$ is not empty && $\mathscr{R}$ is not empty* **do**
4   **for** $j \in \mathscr{R}$ **do**
5   Find the minimum power to achieve capacity gain: $P^j_{\min} = \min_{i \in S}\{P^{j,i}_{\min}\}$;
6   Get N_j: $N_j = \min\{N_j, T_j, P_{\max}/P^j_{\min} - \sum_i I_{i,j}\}$;
7   **if** $N_j \leq 0 \parallel P_{\max} \leq P^j_{\min}$ **then**
8   Remove j from $\mathscr{R}$;
9   **end**
10   **end**
11   **if** $|\mathscr{R}| = 0$ **then**
12   break ;
13   **end**
14   Calculate $w^{i,j}_{s,r}$ by setting $P_{j,i} = P_{\max}/(N_j + \sum_i I_{i,j})$;
15   Calculate $w^{i,i}_{s,d}$ by setting $P_{i,i} = P_{\max}/(N_i + \sum_j I_{j,i})$;
16   Initialize bipartite graph $\mathscr{G}$ with set $\mathscr{S}$ and set $\mathscr{R} \cup \mathscr{D}$ and link capacity assigned as weights;
17   Compute the maximum weight matching ;
18   **for** $i \in \mathscr{S}$ **do**
19   **if** *source i is matched to relay j* **then**
20   Remove source i from $\mathscr{S}$;
21   Set $I_{i,j} = 1$ and $T_j = T_j - 1$;
22   **end**
23   **end**
24   **for** $j \in \mathscr{R}$ **do**
25   **if** *j is not matching saturated* **then**
26   Set $N_j = N_j - 1$;
27   **end**
28   **end**
29 **end**
30 **if** $|\mathscr{S}| \geq 0$ **then**
31   Set $I_i = 1$, for all $i \in \mathscr{S}$;
32 **end**

relay power $P^{i,j}_{\min}$ required to achieve more capacity than by the direct transmission, according to (4) and (5).

In Lines 16–17 of Algorithm 1, maximum weight matching is executed on the constructed bipartite graph. The bipartite graph is constructed as a undirected complete bipartite graph $G(\mathscr{A} \cup \mathscr{B}, E)$. As discussed, the disjoint set $\mathscr{A}$ consists of all the source nodes, while the other disjoint set $\mathscr{B}$ is the union of the relay nodes and destination nodes. The edge between source node i and destination node j indicates that node i chooses to transmit directly to node j; the edge between source node i and relay node j indicates that node i chooses node j as relay and node j will relay symbols to the destination. In this graph, there are actually N_j nodes for one relay, as given in Line 6 in Algorithm 1. The weight of each edge is the capacity achieved by transmitting using the link, which can be calculated and assigned before the matching computation. During every iteration, we check whether or not a relay has been assigned to any source. If a relay BS j has not been matched to any source BSs, we will decrease its service capacity N_j, which is the number of source BSs that this relay serves. By decreasing service capacity, more power will be available for the candidate source BSs.

After the I-variables are determined as in Algorithm 1, the sources are divided into two sets: one set consists of the sources that transmit directly without using any relays, denoted by $\mathscr{S}_1$; the other set consists of the sources that transmit using one relay, denoted by $\mathscr{S}_2$. For each BS i in $\mathscr{S}_2$, its relay is denoted by r_i. The second phase of the centralized algorithm is to solve the power allocation problem, which can be shown to be a convex problem. The power allocation problem in the second phase, which is presented as

$$\max \sum_{i \in \mathscr{S}_1} w^{i,i}_{s,d} + \sum_{i \in \mathscr{S}_2} w^{i,r_i}_{s,r} \tag{24}$$

$$s.t. \sum_{j=1}^{M} P_{i,j} \leq \bar{P}_i, \text{ for all } i \in \{1, 2, \cdots, M\} \tag{25}$$

$$0 \leq P_{i,j} \leq P_{\max}, \text{ for all } i, j \in \{1, 2, \cdots, M\}. \tag{26}$$

This power allocation problem can be solved by many convex optimization methods, such as gradient, interior point, or Newton method [6].

5.2 Distributed algorithm

The centralized algorithm requires a central controller to gather all the channel information and execute the algorithm. It may not be applicable when there is no such centralized entity in the FSO network. In this section, we present a distributed greedy algorithm, where each BS only uses the CSI of its own channels.

With knowledge of the channel gains, a source will always prefer to transmit through the best channel. Hence, for source BS i, we create a preference list according to channel gains $h_{i,j}$; for relay j BS, we also create a preference list according to channel gains $h_{j,i}$. Then, we have two sets: one set includes all the source nodes; the other set includes all the relay or destination nodes. Each source node will select one node from the other set based on the preference lists. Given these preference lists, the problem of determining the I-variables can be treated as a *stable marriage problem* and we can solve it with the DiEGS algorithm [7]. There are two parts of this algorithm: one part called Men-procedure and the other part called Women-procedure. The Men-procedure will be executed in each source BS, and the Women-procedure will be executed in each relay and destination BS. The DiEGS algorithm will produce a stable matching between two sets of BSs, so that there does not exist any alternative pair of BSs in which both of them are better off, given their preference lists [7].

In our case, the size of two parts is not equal. However, it is known that an instance of the stable marriage problem with sets of unequal size has exactly the same set of stable matchings as the same instance with the unmatched nodes deleted. Hence, with some modification of the DiEGS algorithm, we can distributedly solve the relay selection problem in polynomial time.

Next, we need to solve the power allocation problem in a distributed manner, which is given in (24)–(26). For each BS, we have local variables $P_{i,i}$ and $P_{i,j}$. For BS i in $\mathscr{S}_2$, variable $P_{j,i}$ is the power that relay BS allocates to assist its transmission, which is not local. We introduce auxiliary variables $t_i^\star$ to localize capacity $w_{s,r}^{i,r_i}$ and $P_i^\star$ to localize power allocation at the relay. The power allocation problem becomes

$$\max \sum_{i\in\mathscr{S}_1} w_{s,d}^{i,i} + \sum_{i\in\mathscr{S}_2} t_i^\star \tag{27}$$

$$s.t. \sum_{j=1}^{M} P_{i,j} \le \bar{P}_i, \forall\, i \in \mathscr{R}\cup\mathscr{D} \tag{28}$$

$$0 \le P_{i,j} \le P_{\max}, \forall\, i \in \mathscr{B}, j \in \mathscr{S} \tag{29}$$

$$\frac{B}{2}\log_2\left(1+\frac{|h_{i,r_i}|^2 P_{i,i}}{\sigma^2}\right) \ge t_i^\star, \forall\, i \in \mathscr{S}_2 \tag{30}$$

$$\frac{B}{2}\log_2\left(1+\frac{|h_{i,i}|^2 P_{i,i}}{\sigma^2}+\frac{|h_{r_i,i}|^2 P_i^\star}{\sigma^2}\right) \ge t_i^\star, \forall\, i \in \mathscr{S}_2 \tag{31}$$

$$t_{r_i,i} = t_i^\star, t_{j,i} = 0, \forall\, i \in \mathscr{S}_2, j \ne i, j \ne r_i \tag{32}$$

$$P_{r_i,i} = P_i^\star, P_{j,i} = 0, \forall\, i \in \mathscr{S}_2, j \ne i, j \ne r_i, \tag{33}$$

where the subscription of $t_{r_i,i}$ indicates that the power allocation is determined by relay r_i.

We next take a *dual decomposition* approach to obtain a distributed algorithm for power allocation [16]. Applying the Lagrangian method, we show the original problem can be decomposed into subproblems with only local variables. For a BS in set $\mathscr{S}_1$, we have the local maximization problem as

$$\max L_{1,i} = w_{s,d}^{i,i} + \lambda_{1,i}\left(\bar{P}_i - \sum_j P_{i,j}\right) + \boldsymbol{\gamma}_{1,i}^T \mathbf{t}_i + \boldsymbol{\gamma}_{2,i}^T \mathbf{P}_i, \forall\, i \in \mathscr{S}_1. \tag{34}$$

where $\lambda_{1,i}, \boldsymbol{\gamma}_{1,i}, \boldsymbol{\gamma}_{2,i}$ are all Lagrange multipliers and $\mathbf{P}_i = [P_{i,1}, P_{i,2}, \cdots, P_{i,m}]^T$ is the power allocation vector. In this paper, we use bold letters to denote vectors and $(\cdot)^T$ denotes the transpose operation of a matrix. The local dual problem is to minimize a function $g_{1,i}(\lambda_{1,i})$, which is obtained as the maximum value of the Lagrangian solved in (34) for given $\lambda_{1,i}$'s.

For a BS in set $\mathscr{S}_2$, we have the local maximization problem, which is more complicated since its relay power is determined by the relay BS.

Algorithm 2: Distributed Relay selection and Power allocation Algorithm

Initialize the channel gains and obtain the preference lists of source BSs ;
Run the Men- or Women-procedure of DiEGS and determine the I-variables ;
Set $t = 0$, initialize $\gamma_{1,i,j}(0)$, $\gamma_{2,i,j}(0)$ to some value ;
while *termination criterion not met* **do**
  Each BS solves (34) or (35) locally and sends solution to related BSs ;
  Update prices as in (38) and (39) and announce new prices to related BSs ;
  Set $t \leftarrow t+1$;
end

$$\begin{aligned}\max\ L_{2,i} = {} & t_i^\star + \lambda_{1,i}\left(\bar{P}_i - \sum_j P_{i,j}\right) \\ & + \lambda_{2,i}\left(\frac{B}{2}\log_2\left(1+\frac{|h_{i,r_i}|^2 P_{i,i}}{\sigma^2}\right) - t_i^\star\right) \\ & + \lambda_{3,i}\left(\frac{B}{2}\log_2\left(1+\frac{|h_{i,i}|^2 P_{i,i} + |h_{r_i,i}|^2 P_i^\star}{\sigma^2}\right) - t_i^\star\right) \\ & - \gamma_{1,r_i,i}\cdot t_i^\star - \gamma_{2,r_i,i}\cdot P_i^\star + \boldsymbol{\gamma}_{1,i}^T \cdot \mathbf{t}_i \\ & + \boldsymbol{\gamma}_{2,i}^T \cdot \mathbf{P}_i, \forall\, i \in \mathscr{S}_2,\end{aligned} \tag{35}$$

where $\lambda_{1,i}, \lambda_{2,i}, \lambda_{3,i}, \boldsymbol{\gamma}_{1,i}, \boldsymbol{\gamma}_{2,i}$ are Lagrange multipliers. The local dual problem is

$$\min\ g_{2,i}(\lambda_{2,i}, \lambda_{3,i}) = L_{2,i}(\mathbf{P}_i^*, \mathbf{t}_i^*, \lambda_{2,i}, \lambda_{3,i}), \tag{36}$$

where $\mathbf{P}_i^*$ and $\mathbf{t}_i^*$ are the solutions to (35). Thus, the dual objective is defined as the maximum value of the Lagrangian solved in (35) over $\mathbf{P}_i$ and $\mathbf{t}_i$.

The master problem is given by

$$\min\ g(\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2) = \sum_i (L_{1,i} + L_{2,i}). \tag{37}$$

The optimal value of (34) and (35) for given sets of $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$ defines the dual function $g(\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2)$, and this master problem can be solved with the following iterative updates:

$$\gamma_{1,i,j}(t+1) = \gamma_{1,i,j}(t) - \alpha(t_{j,i}(t) - t_i(t)^\star) \tag{38}$$

$$\gamma_{2,i,j}(t+1) = \gamma_{2,i,j}(t) - \alpha(P_{j,i}(t) - P_i(t)^\star). \tag{39}$$

Finally, the distributed algorithm for power allocation is as follows: first, initialize $\gamma_{2,i,j}(0)$, $\gamma_{2,i,j}(0)$ to some value; then, each BS solves its local maximization problem and sends its solution to the related BSs (determined in the step of relay selection). Each BS updates its prices γ-value iteratively and then sends the new prices to other coupled BSs. The algorithm terminates when convergence is achieved or when a maximum number of iterations is reached. The distributed relay selection and power allocation algorithm are presented in Algorithm 2.

Table 1 Simulation parameters

Symbol	Definition
$\lambda = 1{,}550\,\text{nm}$	Wavelength
$D_r = D_t = 0.1\,\text{m}$	Rx. and Tx. Aperture diameter
$K = M = 20$	Number of FSO BSs in the area
$B = 10\,\text{MHz}$	Bandwidth
$R = 5\,\text{Km}$	Radius of area
$P_{\max} = 0.5\,\text{W}$	Peak power constraint
$\bar{P}_i = 2\,\text{W}, \forall\, i$	Power budget for FSO BS i
$T_i = 3, \forall\, i$	Number of transceivers on FSO BS i

Table 2 Atmospheric attenuation coefficient α

Weather condition	α (dB/km)
Clear	0.48
Light fog	13
Clear	0.96
Dense fog	73
Haze	2.8
Deep fog	309

6 Performance evaluation

We evaluate the performance of the proposed algorithms using MATLAB simulations. In the simulations, the FSO BSs are randomly placed in an area of radius R. We assume a sufficient number of transceivers are equipped, and FSO BSs are able to communicate with any other BSs. In one half of this area, there is clear weather; the other half of this area suffers from fog. We calculate channel gains as in Sect. 3.1. The simulation parameters are listed in Table 1 [17]. The atmospheric attenuation coefficients are related to weather, and the values are listed in Table 2 [17].

We also evaluate the upper bound that is obtained by the RLT-based method. However, we find the upper bounds not tight for the scenarios considered in the simulations. This is because the I-variables take noninteger values, and the solution achieved by the RLT-based approach is not feasible. We will present the upper bound results in the discussion of the results, but omit the RLT results in the plots.

In Fig. 2, we evaluate the performance of the two proposed algorithms along with a simple noncooperative scheme and examine the impact of the number of FSO BSs on the total system throughput. It can be seen that the proposed algorithms achieve much higher network-wide throughput than direct transmission. The centralized algorithm has the best performance since it has all the channel information in the network. The distributed algorithm outperforms the noncooperative scheme, although achieves a lower throughput than the centralized algorithm, due to the fact that the distributed

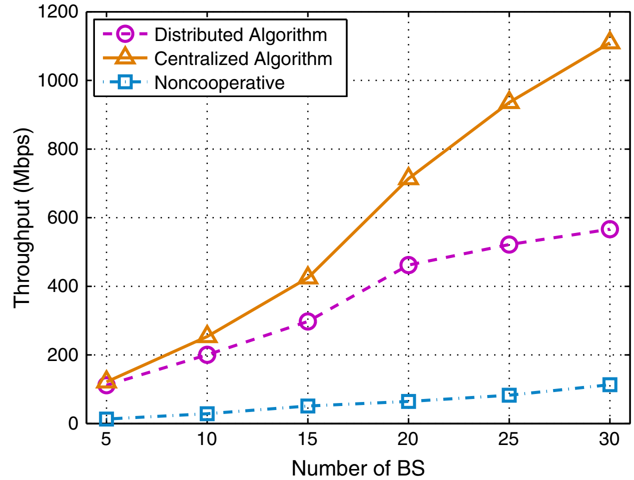

Fig. 2 Throughput versus number of FSO BSs

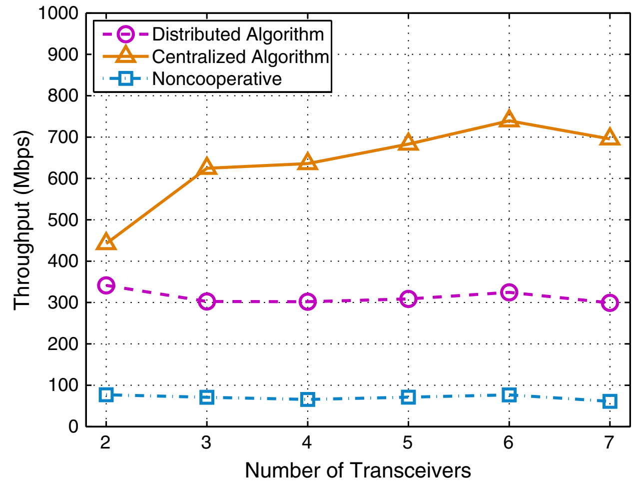

Fig. 3 Throughput versus number of FSO transceivers

algorithm only relies on the knowledge of the BS's local CSI. As the network size increases, the advantage of centralized algorithm becomes more obvious, but it would be more challenging to obtain up-to-date global CSI. The upper bounds obtained from the RLT method are 0.494, 2.662, 5.238, 11.346, 15.729, 24.583 Gbps, when the number of FSO BSs is increased from 5 to 30, respectively, which are not tight when the number of FSO BSs is large.

We also examine the impact of the number of FSO transceivers at each BS on the total system capacity. The number of BSs is set to be 20 in these simulations. In Fig. 3, we find that when the number of transceivers is greater than six, the average throughput of the three algorithms all starts to decrease. This is because when the number of BSs that a relay BS serves is too large, the power that the relay BS can allocate to each BS becomes too small. However, before this critical point, the average throughput increases with the number of transceivers for the centralized algorithm. It is

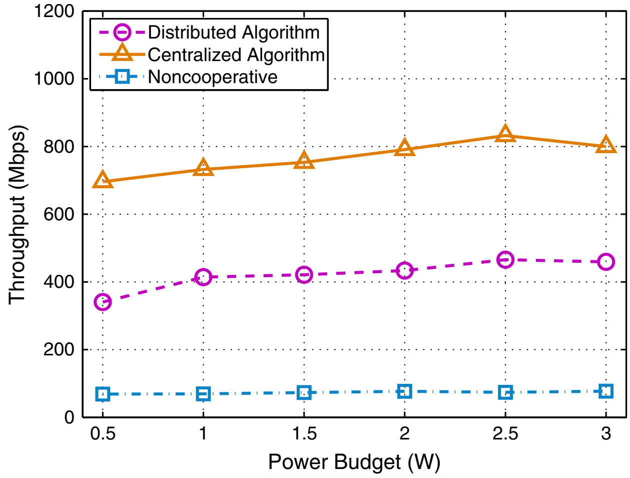

Fig. 4 Throughput versus power budget

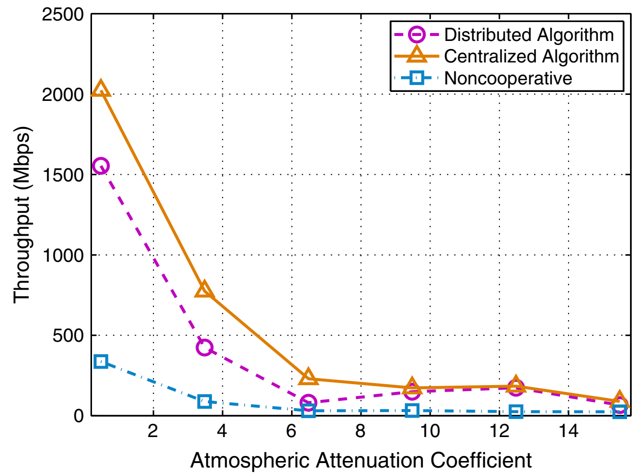

Fig. 5 Throughput versus attenuation coefficient α

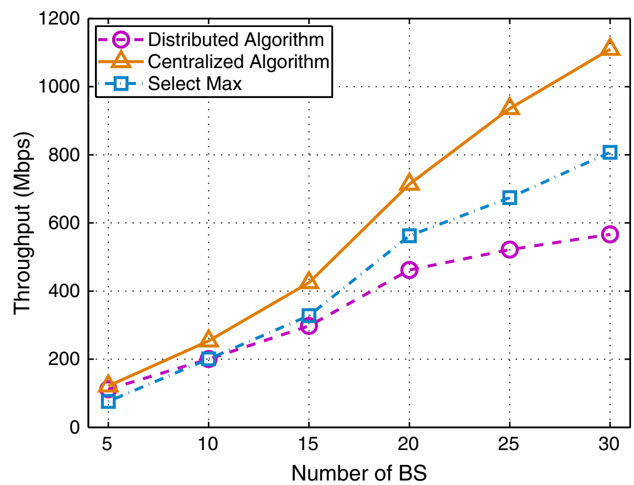

Fig. 6 Throughput versus number of FSO BSs

interesting to see that the number of transceivers has little impact on the distributed algorithm and the noncooperative scheme, indicating that the system has not been fully utilized by these two algorithms. In these simulations, the upper bounds obtained by the RLT method are 10.89, 11.28, 11.07, 10.71, 11.74, 11.52 Gbps, when the number of FSO transceivers is increased from 2 to 7, respectively. It can be seen that the upper bound is still loose in this case.

Next, we examine the impact of the power budget $\bar{P}_i$ available at each BS. To fully examine the impact of the power budget, we set the number of transceivers to five (as observed in Fig. 3). In Fig. 4, we increase $\bar{P}_i$ from 0.5 W to 3 W and plot the total network throughput. It can be seen from the figure that $\bar{P}_i$ has no impact on the noncooperative scheme. On the other hand, as $\bar{P}_i$ is increased from 0.5 W to 2.5 W, the throughput of the FSO network increases when both the centralized and distributed algorithms are used. Due to the limited number of transceivers, the network throughput stops increasing when the power budget is larger than 2.5 W.

We also investigate the impact of weather at each BS location on the total system capacity. We change the weather condition from very clear to foggy. The results are plotted in Fig. 5. As expected, system capacity decreases as weather gets worse. When weather condition is from very clear to hazy, our algorithms outperform the noncooperative scheme with considerable gains. However, after the atmospheric attenuation coefficient α becomes larger than about four, as shown in Fig. 5, the system throughput decreases drastically although our algorithms still achieve better performance. These simulation results show that cooperative schemes can achieve larger throughput, especially when the LOS path is severely affected or not available at all.

The other physical layer parameters in Table 1 can also be changed in the simulations. For example, we change the wavelength from 850 to 1,550 nm. We find that the difference of the total network capacity obtained by using the different wavelength bands is not much obvious. The network-wide capacity obtained from the centralized method, when the wavelength is changed to 1,550 nm, is 716.75, 673.20, 664.71, 620.86, 52.20, 737.18 Mbps, respectively.

Finally, we compare the proposed algorithms with an existing scheme, and the results are presented in Fig. 6. The relaying protocol in [8], termed *Select Max*, always selects a relay with the maximum minimum SNR of the path's intermediate links, i.e.,

$$\arg\min_r \{\mathrm{SNR}_{s,r}, \quad \mathrm{SNR}_{r,d}\}. \tag{40}$$

In this scheme, every source BS uses one relay, and the same power is used for both source BS and relay BS transmissions. This scheme is a centralized one and thus achieves better performance than the proposed distributed algorithm, especially when the network size becomes large. In the case of small network sizes, this scheme has almost the same performance as the proposed distributed algorithm. Under the same scenario when there is centralized control, our proposed centralized algorithm outperforms Select Max in all the scenarios simulated with considerable gains.

7 Conclusion

In this paper, we investigated the problem of maximizing the FSO network throughput under the constraints of a limited power budget and a limited number of FSO transceivers. A centralized algorithm and a distributed algorithm were developed and compared with the noncooperative scheme. Our simulation study showed that the proposed centralized algorithm achieved the greatest capacity but it required a central controller, while the proposed distributed algorithm can be adopted to achieve a superior performance over the noncooperative scheme if centralized coordination is not available.

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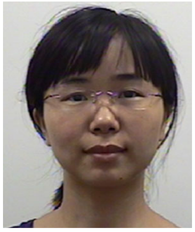

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