QoS-Aware Power Allocation for Multi-UAV Aided Networks

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Abstract. UAV base stations (UAVBS's) have been proposed as a revolution for the new architecture of 5G networks. The UAVBS's can be deployed as access points to provide wireless services to users in emergency scenarios. However, it is challenging to solve the highly coupled problem for UAVBS deployment and power allocation. In the meanwhile, the hybrid analog and digital beamforming is leverage to reduce the hardware cost for beamforming in 5G networks. In this work, we first use k-means algorithm to solve the 3D placement of UAVBS's by exploiting the optimal coverage altitude. Next, power allocation problem is resolved using the difference-of-two-convex functions (D.C.) programming algorithm. Furthermore, the quality of service (QoS) for each user is guaranteed by adjusting the transmitted power. Finally, extensive experiments are conducted to demonstrate the feasibility of the proposed algorithm.

1. Introduction

Unmanned aerial vehicle base stations (UAVBS's), as one of the most promising technologies, have been widely used in some specific environments to support the emergency wireless communications. For instance, UAVBS's are deployed in a post-disaster area with unknown user distribution to support the temporary communications by taking the advantage of the high mobility and low cost [1]. Although the proposed algorithm outperforms the baseline spiral path in terms of the total number of users served, it fails to mention the quality of the communication.

In a large area, it usually requires multiple UAVBS's to cover the demanded users. Due to the complexity of the three-dimensional (3D) mobility, it is challenging to optimize the policy for multiple UAVs by considering the co-channel interference [2][3]. In [4], a deep learning method was proposed to construct the optimal UAVBS deployment. However, it definitely requires large-scale training dataset which is not feasible in practical environment. Moreover, neural networks are not capable of reasoning and cannot interpret the results. If special conditions are emerged in an emergency paralyze machine learning, it is severe to handle the corresponding problems. Thus, a low-complexity deployment algorithm is urgently required for UAVBS systems.

Furthermore, the data traffic is extremely high in 5G networks. As a result, the bandwidth is demanded to be improved for the UAVBS to support the large-scale data transmission. As a promising solution, millimeter wave (mmWave) is used in 5G networks since the higher frequency can support a larger bandwidth. Unfortunately, the higher frequency may result in heavy pathloss. Thus, beamforming technique is proposed to overcome the severe pathloss in 5G networks. However, the conventional fully-digital beamforming systems are not intractable due to the high cost and power consumption. More specifically, conventional beamforming requires one RF chain for one antenna, which is unaffordable in practice. To cope with this challenge, hybrid analog and digital beamforming was proposed in [5].

In contrast to the fully-digital beamforming systems, hybrid precoding reduces the number of RF chains by taking the advantage of the multiple phase shifters and mixers. [6] designed the hybrid
precoding for UAVBS's using the training data by machine learning-based algorithm. It requires iterative optimization which may cause high latency due to the high complexity.

On the other hand, power allocation is also an important problem for the co-channel interference (CCI) elimination. In [7], an energy-efficient power allocation approach was developed to maximize the energy efficiency (EE). However, the spectral efficiency (SE) is the demanded metric to be maximized. [8] constructed a hybrid precoding design and power allocation using the zero-forcing algorithm while the quality of service (QoS) for each user cannot be guaranteed.

In this work, a hybrid precoding method is proposed for UAVBS's to reconstruct the communications in emergency scenarios. More specifically, we implement a novel deployment method for UAVBS's placement. Next, a hybrid analog and digital precoding method is leveraged to reduce the number of RF chains. After that, a power allocation scheme is developed by using the difference of two convex function (D.C.) programming algorithm.

Finally, the contributions of this work can be summarized as follows:

- The UAVBS's deployment problem is solved using k-means algorithm by considering the practical pathloss channel model. The 3D placement of UAVBS's is separately addressed to optimize the user association by considering the CCI.
- Hybrid precoding and power allocation are jointly optimized using the D.C. programming by considering the large-scale pathloss and beamforming gain.
- Extensive simulations are conducted to demonstrate the effectiveness of the proposed QoS-aware power allocation hybrid precoding algorithms for UAVBS systems.

The remainder content of this paper is organized as follows. Section II presents the system model and formulates the problems for UAVBS systems. After that, the UAVBS deployment is separately optimized in 3D space using k-means algorithm by considering the pathloss channel model in Section III. As the deployment problem is solved, the hybrid precoding and QoS-aware power allocation are jointly optimized using the D.C. programming algorithm in Section IV. Next, the computer simulation results are elaborated in Section V and the conclusion is summarized in the end.

2. System Model and Problem Formulation

In the sequel, the system model as well as channel model for UAVBS are presented. Furthermore, the optimization problem is derived.

2.1 Air-to-Ground (ATG) Channel

As shown in Fig. 1, $K$ UAVBS's are deployed over the users to support the emergency communications for $N$ users. Specifically, $N_k$ users are assigned to the $k$-th UAVBS. Thus, we have $\sum_{k=1}^{K} N_k = N$.

![Fig. 1. The schematic diagram of proposed system.](image)

The pathloss between the $k$-th UAV and the $n_l$-th user can be formulated as follows:
Recalling Equation (1), the pathloss can be calculated according to the positions of the users and UAVBS. Denote \( p_k^U = [x_k^U, y_k^U, z_k^U] \) and \( p_k^E = [x_k^E, y_k^E, 0] \) by the 3D location of the \( k \)-th UAVBS and its \( u \)-th user, respectively. Thus, the horizontal and vertical distance between the \( k \)-th UAVBS to its \( u \)-th user can be represented by the
\[
d_{k,u} = \sqrt{(x_k^U - x_k^E)^2 + (y_k^U - y_k^E)^2},
\]
and
\[
h_{k,u} = z_k^U.
\]

2.2 Hybrid Precoding System Design
It is assumed that a base station has \( N_{BS} \) antennas and \( N_{RF} \) chains when it communicates with \( N_k \) users. Each user is equipped with \( N_{M_S} \) antennas. For the \( k \)-th UAVBS, we are concerned with multi-user beamforming case where the UAVBS communicates with each user via one data stream. Thus, the number of minimally required RF chains is equal to the number of users, i.e., \( N_k \).

We assume the digital precoder is \( \mathbf{F}_k = [f_k,1, \cdots, f_k,N_k] \) followed by the analog precoder \( \mathbf{V}_k = [v_k,1, \cdots, v_k,N_k] \). The precoded signal transmitted by the UAVBS is
\[
\mathbf{x}_k = \mathbf{V}_k \mathbf{F}_k \mathbf{s}_k,
\]
with \( s_k \) being the data stream \( \mathbb{E} [s_k s_k^H] = \frac{P}{N_k} I_{N_k} \)

Then, the decoded signal can be represented as
\[
y_{k,u} = w_{k,u}^H H_{k,u} \sum_{u=1}^{N_k} \mathbf{V}_k f_k, u s_{k,u} + w_{k,u}^H n_{k,u}.
\]

The virtual channel model is expressed as
\[
H_{k,u} = \sqrt{\frac{N_{BS} N_{M_S}}{L_{k,u}}} \sum_{l} \alpha_{k,u,l}^\prime a_{M_S}(\theta_{k,u,l}^\prime) a_{BS}^H(\theta_{k,u,l}^\prime),
\]
where \( \alpha_{k,u,l} \) is the complex gain of the \( l \)-th path. We assume the UAVBS uses the uniform linear array antennas. The array response vectors in Equation (2) are given by
\[
a(\theta) = \left[ 1, e^{j \frac{2\pi}{N} \sin \theta}, \cdots, e^{j (N_{BS} - 1) \frac{2\pi}{N} \sin \theta} \right].
\]

2.3 Problem Formulation
The transmitted power is set to be \( P_{k,u}^T \). The received signal power is formulated as
\[
\beta_{k,u} = P_{k,u}^T - L_{k,u}.
\]

Thus, the spectral efficiency of the \( u \)-th user under the \( k \)-th UAVBS can be presented as follows:
\[
R_{k,u} = \log_2 \left( 1 + \frac{\beta_{k,u} |w_{k,u} H_u F_R F_{R}^H|^2}{\sum_{u' \neq u} \beta_{u'} |w_{k,u} H_u F_R F_{R}^H|^2 + \sigma_u^2} \right).
\]

The optimization problem in this work is formulated by
where $C_1$ and $C_2$ are the analog constraints for the transmitter and receiver, respectively. $C_3$ is the power normalization on each RF chain while $C_4$ constrains the total power consumption. Finally, the QoS of each user is guaranteed with a threshold $\lambda_{k,u}$.

The hybrid beamforming design and power allocation highly depend on the locations of the UAVBS's. Thus, we first need to address the locations of the UAVBS's according to the fixed positions of the users.

### 3. 3D UAVBS deployment

In this section, the positions of the UAVBS's are separately addressed using the k-means algorithm based on the proposed constraints.

#### 3.1 Horizontal placement by K-Means algorithm

K-means algorithm is the unsupervised method to classify the clusters of objects. Here, a user association method is proposed using k-means by calculating the horizontal distance between the UAVBS and users. First, the altitude of the UAVBS is neglected. We need to deploy the UAVBS's to satisfy the following equation:

$$ \text{maximize} \quad R_{td}(W, V, F, p) $n_s$$

subject to

$$ C_1 : \|w_{k,u}\|^2 = 1/N_T, i = 1, 2, \cdots, N_T; $$

$$ C_2 : \|w_{k,u}\|^2 = 1/N_R, j = 1, 2, \cdots, N_R; $$

$$ C_3 : \|V_kf_{k,u}\|^2 = 1; $$

$$ C_4 : \sum_{k=1}^{K} \sum_{u=1}^{M_k} p_{k,u} \leq N_U; $$

$$ C_5 : R_{k,u} \geq \lambda_{k,u}, \quad (3) $$

Altitude Optimization

As the horizontal positions of the UAVBS's fixed, we now consider the optimally deployed altitudes. Recalling the Equation (1), the optimal altitude can be derived by

$$ \frac{\partial L_{k,u}^\text{max}}{\partial h_k} = 0, \quad (4) $$

where $L_{k,u}^\text{max}$ is the farthest user under the $k$-th UAVBS. Intuitively, the pathloss of the farthest user should be considered for the altitude adjustment.

In practical, it is particularly challenging to analytically solve the Equation (4). As a result, we can numerically calculate the locally optimum for the altitude derivation.

#### 3.2 Constraints of UAVBS's

Now we consider the constraints for the UAVBS deployment. Since co-channel interference exists among different UAVBS's, the user should be only assigned to one UAVBS at one instant. Furthermore, the maximal coverage radius and altitude of the UAVBS should be also constrained. Thus, the constraints are formulated as:
where \( R_m \) and \( H_m \) are the given maximal coverage radius and altitude, respectively. In addition, the safety distance of the UAVBS’s should be satisfied. This constraint can be represented as

\[
\| p_k^U - p_j^U \|_2 \geq D_m, \text{ for } \forall k, j = 1, \ldots, K,
\]

where \( D_m \) is the given minimal safety distance between two UAVBS's.

4. Hybrid precoding design and QoS-aware power allocation

4.1 Hybrid precoding algorithm for UAVBS

We begin with the analog beamforming design for both transmitter and receiver. It is well known that distinct array response vectors are asymptotically orthogonal as the number of antennas in an antenna array goes to infinity [9], i.e.,

\[
\lim_{N \to +\infty} \alpha_T^H(\phi_{k,u}, \theta_{k,u}) \cdot \alpha_T(\phi_{k,v}, \theta_{k,v}) = \delta(k - \ell)\delta(u - v).
\]

However, since the antenna number is finite in practice, the residual interference must be considered in the analog precoding design. Recalling the channel model presented in Equation (2), we can asymptotically orthogonalize the transmitted signals by optimizing the design of \( w_{k,u} \) and \( \psi_{k,u} \):

\[
\{ w_{k,u}^*, \psi_{k,u}^* \} = \arg \max_{\tilde{w}_{k,u}, \psi_{k,u}} \sum_{k=1}^{K} \sum_{u=1}^{M_u} \log_2 (1 + \text{SINR}(\tilde{w}_{k,u}, \tilde{v}_{k,u}))
\]

subject to \( \tilde{v}_{k,u}, \psi_{k,u} \in \mathbb{A}_{k,u}^T \)

\[
\tilde{w}_{k,u}, \psi_{k,u} \in \mathbb{A}_{k,u}^R,
\]

\[
\max \{ M_k \}_{k=1}^{K} < N_{RF},
\]

where

\[
\mathbb{A}_{k,u}^T = \left\{ \alpha_T(\phi_{k,u,1}, \theta_{k,u,1}), \ldots, \alpha_T(\phi_{k,u,L_{k,u}}, \theta_{k,u,L_{k,u}}) \right\},
\]

\[
\mathbb{A}_{k,u}^R = \left\{ \alpha_R(\phi_{k,u,1}, \theta_{k,u,1}), \ldots, \alpha_R(\phi_{k,u,L_{k,u}}, \theta_{k,u,L_{k,u}}) \right\}.
\]

Furthermore, SINR\(_{k,u}\) is given by

\[
\text{SINR}(\tilde{w}_{k,u}, \tilde{v}_{k,u}) = \frac{|\tilde{w}_{k,u}^H H_{k,u} \tilde{v}_{k,u}|^2}{\sum_{j=1, i \neq k}^{N_U} |\tilde{w}_{k,u}^H H_{k,u} V_j|^2 + \sum_{l \neq u} |\tilde{w}_{k,u}^H H_{k,u} \tilde{v}_{k,l}|^2 + \frac{1}{\gamma}}.
\]

With \( \gamma = \sigma_{k,u}^{-1} \). The optimal analog beamforming precoder can be straightforwardly found by exhaustively searching in the feasible sets of \( \mathbb{A}_{k,u}^T \) and \( \mathbb{A}_{k,u}^R \).

In contrast to the conventional ZF hybrid beamforming scheme [10] that requires \( N_{RF} < N_{RF} \), zero-forcing digital precoding scheme is first proposed to transmit data-streams group by group. More specifically, the digital precoder for each block is designed as the inverse of the effective channel of the block:

\[
\mathcal{F}_{k}^{\text{BZF}} = \mathcal{G}_{k}^H (\mathcal{G}_{k} \mathcal{G}_{k}^H)^{-1},
\]

With \( N_{RF} \geq M_k \) where \( \mathcal{G}_{k} = [g_{k,1}^{(k)} \; g_{k,2}^{(k)} \; \cdots \; g_{k,M_k}^{(k)}] \).

To satisfy the constraint \( C_3 \) in Equation (3), power normalization is performed on each \( f_{k,u} \) derived from \( f_{k,u}^{\text{BZF}} = [f_{k,u,1}^{\text{BZF}} \; f_{k,u,2}^{\text{BZF}} \; \cdots \; f_{k,u,M_k}^{\text{BZF}}] \) as
Subsequently, this scheme is referred to as the block zero-forcing (BZF) scheme. It is worth noting that BZF degenerates to [10] if \( K = 1 \), i.e., all users are grouped into one independent group. On the other hand, BZF becomes the analog-only BDMA if \( K = N_t \), i.e., each user forms one group and only analog beamforming is performed.

### 4.2 QoS-Aware Power Allocation Using D.C. Programming

For given analog and digital precoders, we investigate the QoS-aware power allocation \( P \) in Equation (3) by using the D.C. programming technique in this section.

We begin with reformulating Equation (3) as

\[
\max_{P} \sum_{k=1}^{K} \sum_{u=1}^{M_k} R_{k,u}(p)
\]

subject to

\[C_1: \sum_{k=1}^{K} \sum_{u=1}^{M_k} p_{k,u} \leq P; \]

\[C_2: R_{k,u} \geq \lambda_{k,u}.\]

Following the procedures in [11], the problem above can be cast as a D.C. programming problem:

\[
\max_{P} f(P) - g(P)
\]

where

\[
f(\beta) = \sum_{k=1}^{K} \sum_{u=1}^{N_k} \log_2 \left( \sum_{k=1}^{K} \sum_{u=1}^{N_k} \beta_{k,u} \left| g^{(k)}_{k,u} f_{k,u} \right|^2 + \sigma_{k,u}^2 \right),
\]

\[
g(\beta) = \sum_{k=1}^{K} \sum_{u=1}^{N_k} \log_2 \left( \sum_{j=1}^{N_t} \sum_{t=1}^{N_t} \beta_{j,t} \left| g^{(j)}_{k,u} f_{j,t} \right|^2 + \sigma_{k,u}^2 \right).
\]

Since the analog and digital precoders are obtained, both \( f(P) \) and \( g(P) \) are concave in \( P \), i.e., Equation (5) is a D.C. function. Starting from a feasible \( P^{(1)} \), the optimal \( P^{(n+1)} \) at the \( n \)-th iteration is generated as the optimal solution of a convex problem:

\[
\max_{P} f(P) - g(P^n) - \langle \nabla g(P^n), P^n, P^{(n+1)} - P^{(n)} \rangle, \tag{6}
\]

which can be efficiently solved by any existing convex programming software, such as CVX [12]. The computational complexity of Equation (6) is \( O(N^3) \) in each iteration [11].

As \( g(P^n) \) is concave, its gradient \( \nabla g(P^n) \) is also super-gradient:

\[
f(P^{(n+1)}) - g(P^{(n+1)}) \geq f(P^{(n+1)}) - \left[ g(P^{(n)}) + \langle \nabla g(P^{(n)}), P^{(n+1)} - P^{(n)} \rangle \right].
\]

The proof is given in Appendix 1.

Finally, since \( P^{(n+1)} \) is the solution to Equation (5), it follows that

\[
f(P^{(n+1)}) - g(P^{(n)}) \geq f(P^{(n)}) - g(P^{(n)}),
\]

\[
f(P^{(n)}) - g(P^{(n+1)}) \geq f(P^{(n)}) - g(P^{(n)}),
\]

Therefore, the \( (n+1) \)-th solution is always better than the previous one. The iterative process
terminates after $|f(p^{(n+1)}) - g(p^{(n+1)}) - (f(p^{(n)}) - g(p^{(n)}))| \leq \epsilon$ is achieved with a pre-defined threshold $\epsilon > 0$.

5. Simulation results

In Fig. 2, we can observe that the UAVBS’s provide the coverage of the users for emergency communications. We assume 20 users are randomly assigned in a horizontal area with size $400 \times 400$ m$^2$ while four UAVBS’s are deployed to support the communications. As proposed in Section III-C, there is no users among the intersection of the UAVBS’s coverage. As a result, the interference among different UAVBS’s can be minimized by optimizing the deployment.

In Fig. 3, it shows the comparison of the sum-rate between the conventional hybrid beamforming system and the proposed scheme with 6 RF chains serving 6 users. We consider the single-user case where only one user is assigned to the UAVBS at each time. Thus, the interference among different UGVs can be totally neglected. The curve labeled as ”Conventional Zero-forcing” refers to the conventional hybrid precoding with uniform power allocation. It is observed that the ”D.C. Power Allocation” outperforms the ”Conventional Zero-forcing” from 0 dB to 20 dB.
Inspection of Fig. 4 suggests that the proposed D.C. programming algorithm can guarantee the QoS of each user. We set the threshold to be 3 bps/Hz. In contrast, there are approximately 10% of UGVs that cannot be satisfied with required QoS using uniform power allocation algorithm.

6. Conclusion
In this work, a hybrid preocoding scheme is developed to improve the throughput of the UAVBS's. We have proposed a D.C. programming algorithm to ensure the individual QoS. In addition, the deployment problem for the UAVBS's is addressed using k-means with several self-defined constraints. Furthermore, computer simulations are conducted to demonstrate the effectiveness of our proposed algorithms.

Appendix
Proof for Equation (7)
Suppose \( f(p) \) is a concave function on a convex neighborhood \( C \) and differentiable at \( \lambda m \{ p \} \). Then, for every \( y \in C \), we have the following inequality based on the definition of concavity:

\[
\begin{align*}
\frac{f((1-\lambda)p + \lambda y)}{\lambda} &\geq f(p) + \lambda (f(y) - f(p)), \\
\end{align*}
\]

where \( 0 < \lambda < 1 \).

Rearranging the terms and dividing both sides by \( \lambda \), we have

\[
\begin{align*}
\frac{f(p + \lambda(y - p)) - f(p)}{\lambda} &\geq f(y) - f(p).
\end{align*}
\]

Letting \( \lambda \to 0 \), it can be shown that the left hand side of Inequality above converges to \( f'(p) \cdot (y - p) \).

Finally, we have Equation (7) as:

\[
\begin{align*}
f(p) + f'(p) \cdot (y - p) &\geq f(y).
\end{align*}
\]

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