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RESEARCH ARTICLE

K-Means Clustering-Aided Power Control for UAV-Enabled OFDM Networks

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ABSTRACT In this paper, we consider an unmanned aerial vehicle (UAV)-enabled orthogonal frequency division multiplexing (OFDM) network where the UAV acts as an aerial base station and employs the OFDM to transmit individual data to multiple users on the ground. We propose a K-means clustering-aided power control algorithm to maximize the sum-rate of the network under the total transmit power and the minimum rate constraints. The proposed algorithm categorizes N_s subcarriers into K clusters and optimizes the transmit power for the clustered subcarriers with a power splitting factor to decompose the multi-user power allocation problem. Since the number of clusters is far less than the number of subcarriers, the proposed algorithm requires low-computational complexity compared to the conventional water-filling algorithm. Simulation results show that the proposed algorithm provides near-optimal performance with $K = 4$ clusters even for a large number of subcarriers $N_s = 1024$.

INDEX TERMS Unmanned aerial vehicle-enabled network, K-means clustering, power control, sum-rate maximization.

I. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) are promising technologies for future wireless networks [1], [2], [3], [4]. Recently, the IEEE 802.11 working group approved the formation of a topic interest group (TIG) for the AI/ML use in the IEEE 802.11 [5]. The TIG describes use cases for the AI/ML applicability in the IEEE 802.11 standards and investigates the technical feasibility of the AI/ML [6]. In addition, the 3GPP is studying the AI/ML for a new radio (NR) air interface to achieve the requirements for key performance indicators such as latency, reliability, user experience, and others [7], [8].

Generally, the ML algorithms are categorized as supervised learning, unsupervised learning, and reinforcement learning [9]. Supervised learning learns a function that maps an input to an output with labeled data [10]. Unsupervised learning learns a function that represents a hidden structure of an input with unlabeled data [11]. Reinforcement learning learns a function that maximizes a long-term reward with an environment and a set of actions [12]. The K-means clustering is one of the simplest unsupervised learning algorithms that groups unlabeled data into K clusters. Specifically, the K-means clustering algorithm maps data into the nearest cluster centers and finds K cluster centers to minimize the sum of squared distances from data to K cluster centers [9], [11].

To extend the transmission coverage of wireless networks, unmanned aerial vehicles (UAVs) have been employed for various applications such as aerial base stations, relaying stations, and wireless power transfer [13], [14], [15]. Since the UAVs utilize most of their electrical energy to fly [16], the resource allocations should be optimized to maximize communication performance and prolong flight time for the UAV-enabled wireless networks [15], [17], [18], [19], [20].

The joint trajectory design and the transmit power control algorithm were proposed to minimize the outage probability in the UAV relay network [15]. In the mobile

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edge computing (MEC) network with multiple UAVs, the sum-power minimization algorithm was designed by jointly optimizing user association, power control, computation capacity allocation, and location planning [17]. In the UAV-enabled orthogonal frequency division multiple access (OFDMA) networks, the joint trajectory design and the resource allocation algorithm were proposed to maximize the minimum rate of ground users while guaranteeing their specified minimum-rate constraints [18].

In the UAV-aided wireless-powered communication networks (WPCN), a multi-objective optimization problem (MOOP) which optimizes the UAV's 3D position, the transmit power, the time splitting ratio, the uplink transmission time, and the beamwidth angle of the UAV, was proposed to maximize the achievable sum-rate in the uplink and minimize the downlink transmit power simultaneously [19]. In the UAV-enabled MEC, a constrained MOOP which optimizes the transmit power of the devices, computing resource, flying velocity, and 3D path of the UAV was investigated to simultaneously reduce the energy consumption and ensure the safe flight for the UAV [20].

In the multi-UAV-aided MEC networks, the deep reinforcement learning (DRL) based UAV movement, mobile user (MU) association, and MU transmit power control algorithm was proposed to decrease the system latency and the energy consumption [21]. In the UAV-aided WPCN, the DRL-based framework for joint UAV placement and resource allocation was proposed to maximize the long-term federated learning performance considering the limited resources in the network [22]. Since the computing capacity of the UAV is limited, we consider the K-means clustering algorithm that requires lower computational complexity than the DRL algorithm.

The orthogonal frequency division multiplexing (OFDM) divides the data stream into multiple substreams and transmits multiple substreams over different subcarriers. The OFDM eliminates inter-symbol interference because the symbol time on each substream is much greater than the delay spread of the channel [23], [24]. The OFDM data rate can be improved by optimizing the power allocation for subcarriers with a total transmit power constraint [25]. However, the power allocation algorithm for the OFDM with many subcarriers requires high computational complexity since the power allocation executes on a per-subcarrier basis [26], [27].

Several studies have proposed using subcarrier clustering to reduce the complexity of the resource allocations and the beamforming in the OFDMA networks [28], [29], [30]. The cluster, also called the chuck, consists of the adjacent subcarriers. The subcarriers in the same cluster allocate an equal modulation level under an average bit-error-rate (BER) constraint [28] and apply a common transmit beamformer to reduce the number of feedback bits [29]. The joint chunk, power, and bit allocations were proposed to maximize the throughput under the total transmit power constraint [30].

In this paper, we consider a UAV-enabled wireless network where the UAV transmits individual data to multiple users on the ground. The UAV employs the OFDM to mitigate inter-symbol interference in addition to time division multiple access (TDMA) to avoid inter-user interference. We propose a K-means clustering-aided power control algorithm to maximize the sum-rate of the network. The proposed algorithm is composed of subcarrier clustering and power allocation for clustered subcarriers with power splitting. In the UAV-enabled wireless network, the K-means clustering algorithm was employed to cluster users [31], [32]. On the contrary, we apply the K-means clustering algorithm to cluster subcarriers. Unlike existing subcarrier clustering algorithms in [28], [29], and [30], the proposed algorithm can assign non-adjacent subcarriers to the same cluster, which can significantly improve the flexibility and performance of proposed algorithm. The major contributions of this paper are summarized as follows.

- We design the subcarrier clustering to represent the signal-to-noise ratio (SNR) of N_s subcarriers into K cluster centers. The clustered subcarriers are used in the transmit power allocation algorithm to reduce computational complexity.
- We propose the training phase and the test phase of the subcarrier clustering based on the K-means clustering algorithm.
- We propose the power allocation for clustered subcarriers with power splitting to decompose the multi-user power allocation problem into multiple single-user power allocation problems.
- We derive a closed-form expression of the optimal transmit power for clustered subcarriers and the optimal power splitting factor that maximize the sum-rate of the network under the total transmit power and the minimum rate constraints.
- We analyze the computational complexity and the convergence of the proposed algorithm.
- Simulation results show that the proposed algorithm provides near-optimal performance, although the number of clusters is much less than the number of subcarriers.

The remainder of this paper is organized as follows. The system model is described in Section II. The proposed K-means clustering-aided power control algorithm is presented in Section III. Simulation results are given in Section IV. Finally, we conclude this paper in Section V.

II. SYSTEM MODEL

As shown in Fig. 1, we consider a UAV-enabled wireless network where a UAV with N_t antennas acts as an aerial base station to transmit individual data to N_u users with a single antenna on the ground. The horizontal distance from the UAV to the u-th user is d_u, and the maximum transmission coverage of the UAV is d_m. Since the UAV consumes most

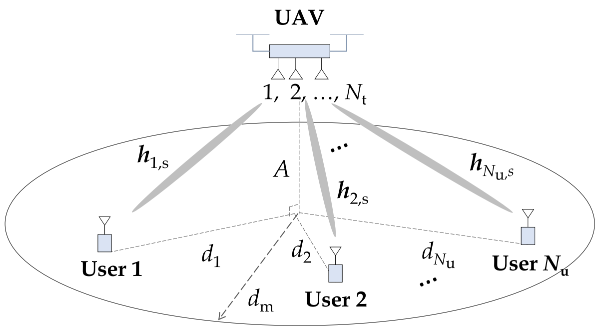

FIGURE 1. **UAV-enabled wireless network.**

of the electrical energy to fly [16], [33], we set the UAV to hover at the center of users[1] with an altitude A to prolong the flight time. Low-complexity algorithms are suitable for the UAV-enabled network by considering the computational capability of the UAV [34], [35], [36]. We employ the OFDM scheme with N_{s} subcarriers and the TDMA scheme for data transmission to avoid inter-symbol interference and inter-user interference, respectively.

The channel response vector from the UAV to the u-th user is represented as

$$\mathbf{h}_{u,s} = \left[h_{u,s,1}, h_{u,s,2}, \cdots, h_{u,s,N_{\mathrm{t}}}\right]^{\mathrm{T}}, \tag{1}$$

where

$$h_{u,s,t} = \frac{1}{\sqrt{N_{\mathrm{s}}}} \sum_{l=0}^{L-1} \sqrt{\nu_{u,l}}\, g_{u,l,t} \exp\left[-j\frac{2\pi ls}{N_{\mathrm{s}}}\right] \tag{2}$$

denotes the channel frequency response on the s-th subcarrier at the t-th transmit antenna with L paths. In (2), the complex channel gain for the l-th path between the t-th transmit antenna of the UAV and the receive antenna of the u-th user is represented as

$$g_{u,l,t} = \sqrt{\frac{K_{\mathrm{R}}}{K_{\mathrm{R}}+1}}\, g + \sqrt{\frac{1}{K_{\mathrm{R}}+1}}\, \bar{g} \tag{3}$$

where g is the deterministic line-of-sight (LoS) term with $|g| = 1$, $\bar{g}$ is the random scattered term which is distributed as a zero-mean unit-variance circularly symmetric complex Gaussian (CSCG) random variable, and K_{R} denotes the Rician factor of the channel. The average channel power from the UAV to the u-th user for l-th path is given by

$$\nu_{u,l} = \delta_l 10^{-\ell_u/10}, \tag{4}$$

where δ_l is the channel power coefficient for the l-th path with $\sum_{l=1}^{L} \delta_l = 1$, and ℓ_u is the air-to-ground (A2G) path-loss from the UAV to the u-th user [37], [38]. The A2G path-loss between the UAV and the u-th user is expressed as

$$\ell_u = \frac{\eta_{\mathrm{LoS}} - \eta_{\mathrm{NLoS}}}{1 + a\exp\left[-b\left(\arctan\left(\frac{A}{d_u}\right) - a\right)\right]} + 10\log\left(d_u^2 + A^2\right) + 20\log\left(\frac{4\pi f_{\mathrm{c}}}{c}\right) + \eta_{\mathrm{NLoS}}, \tag{5}$$

where η_{LoS} and η_{NLoS} are the mean additional losses for LoS and non-line-of-sight (NLoS) terms, respectively, and a and b are constants depending on the type of environment such as suburban, urban, dense-urban, and high-rise urban. The carrier frequency is f_{c}, and the speed of light is c. Here, we omit a time index in the channel response and assume that the channel response vector information is available at the UAV.

The received signal on the s-th subcarrier at the u-th user is represented as

$$y_{u,s} = \sqrt{p_{u,s}}\,\mathbf{h}_{u,s}^{\mathrm{H}}\mathbf{f}_{u,s} x_{u,s} + w_{u,s}, \tag{6}$$

where $p_{u,s}$ indicates the transmit power of the UAV on the s-th subcarrier for the u-th user, $\mathbf{f}_{u,s} = \mathbf{h}_{u,s}/\left\|\mathbf{h}_{u,s}\right\|$ denotes the maximum ratio transmission (MRT) beamformer of the UAV on the s-th subcarrier for the u-th user, $x_{u,s}$ is the transmission signal on the s-th subcarrier for the u-th user with average power $\mathbb{E}\left[|x_{u,s}|^2\right] = 1$, and $w_{u,s}$ is an additive white Gaussian noise (AWGN) on the s-th subcarrier at the u-th user with average power $\mathbb{E}\left[|w_{u,s}|^2\right] = \sigma_{u,s}^2$. The data rate between the UAV and the u-th user is expressed as

$$R_u = \sum_{s=1}^{N_{\mathrm{s}}} \log_2\left(1 + p_{u,s}\gamma_{u,s}\right), \tag{7}$$

where $\gamma_{u,s} = \frac{\|\mathbf{h}_{u,s}\|^2}{\sigma_{u,s}^2}$ is the normalized SNR on the s-th subcarrier at the u-th user. Using (7), we represent the sum-rate of the network as

$$R = \sum_{u=1}^{N_{\mathrm{u}}} R_u. \tag{8}$$

In this paper, we consider the transmit power control of the UAV to maximize the sum-rate of the network under the total transmit power and the minimum rate constraints. The optimal transmit power of the UAV on the s-th subcarrier for the u-th user is obtained by solving the following optimization problem:

$$\begin{aligned} &\max_{p_{u,s}} R \\ &\text{s.t.} \sum_{u=1}^{N_{\mathrm{u}}}\sum_{s=1}^{N_{\mathrm{s}}} p_{u,s} \le P_{\mathrm{t}}, \\ &\quad R_u \ge R_{\mathrm{t}},\ u = 1, \cdots, N_{\mathrm{u}}, \end{aligned} \tag{9}$$

where P_{t} is the total transmit power for the UAV, and R_{t} is the minimum rate constraint for each user. It is known that a conventional water-filling algorithm obtains the optimal transmit power of the UAV by solving (9) with $\mathcal{O}\left(N_{\mathrm{u}}N_{\mathrm{s}}\right)$ computational complexity [23], [39]. However, the conventional water-filling algorithm is infeasible when the

[1] Since the A2G path-loss of the u-th user (5) is related to the squared distance between the UAV and the u-th user, we set the position of the UAV to the center of users to minimize the sum of squared distances from the UAV to the users.

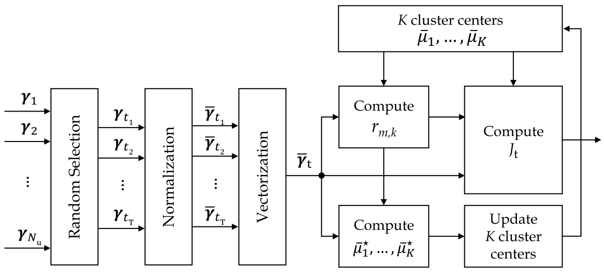

FIGURE 2. Block diagram of the training phase for the subcarrier clustering.

number of subcarriers or the number of users in the network is too large. Therefore, we propose a K-means clustering-aided power control algorithm that provides near-optimal performance with low-complexity.

III. PROPOSED ALGORITHM

In this section, we propose the K-means clustering-aided power control algorithm. The proposed algorithm is composed of subcarrier clustering and power allocation for clustered subcarriers. The subcarrier clustering categorizes N_{s} subcarriers into K clusters using the K-means clustering algorithm. The power allocation optimizes the transmit power for clustered subcarriers with a power splitting factor to maximize the sum-rate of the network.

A. SUBCARRIER CLUSTERING

The subcarrier clustering employs the K-means clustering which is one of an unsupervised learning algorithms, and maps N_{s} subcarriers to K cluster centers. Considering the fact that the computing capacity of the UAV is limited, the K-means clustering is adequate for the subcarrier clustering in the UAV-enabled OFDM network since it is relatively simple to implement [40], [41].

The subcarrier clustering consists of a training phase and a test phase. In the training phase, the subcarrier clustering learns K cluster centers with the training dataset to minimize distortion due to clustering. In the test phase, the subcarrier clustering assigns N_{s} subcarriers to the nearest cluster according to the SNR of N_{s} subcarriers and K cluster centers.

1) TRAINING PHASE FOR SUBCARRIER CLUSTERING

Fig. 2 shows the block diagram of the training phase for the subcarrier clustering. During the training phase, T users are randomly selected among N_{u} users to generate the training dataset. The SNR vector of the t_i-th user in the training dataset is represented as

$$\boldsymbol{\gamma}_{t_i} = \left[\gamma_{t_i,1},\ \gamma_{t_i,2}, \cdots,\ \gamma_{t_i,N_{\mathrm{s}}}\right]^{\mathrm{T}}, \tag{10}$$

where $\gamma_{t_i,s}$ denotes the SNR on the s-th subcarrier of the t_i-th user. The average SNR of the user depends on the A2G path-loss related to the location of the user. We apply normalization to adjust the range of the SNR of users from 0 to 1 because the users are randomly distributed within the maximum transmission coverage d_{m}. The normalized SNR vector of the t_i-th is represented as

$$\bar{\boldsymbol{\gamma}}_{t_i} = \frac{\boldsymbol{\gamma}_{t_i}}{\hat{\gamma}_{t_i}}, \tag{11}$$

where $\hat{\gamma}_{t_i} = \max_s \gamma_{t_i,s}$ is the maximum SNR of the t_i-th user among N_{s} subcarriers. The training dataset is obtained by vertically stacking the normalized SNR vectors of T users as

$$\bar{\boldsymbol{\gamma}}_{\mathrm{t}} = \mathrm{vec}\left(\left[\bar{\boldsymbol{\gamma}}_{t_1}, \bar{\boldsymbol{\gamma}}_{t_2} \cdots, \bar{\boldsymbol{\gamma}}_{t_{\mathrm{T}}}\right]\right), \tag{12}$$

which becomes a $TN_{\mathrm{s}} \times 1$ column vector.

We represent K cluster centers as

$$\bar{\boldsymbol{\mu}} = \left[\bar{\mu}_1,\ \bar{\mu}_2, \cdots,\ \bar{\mu}_K\right]^{\mathrm{T}}, \tag{13}$$

where $0 \leq \bar{\mu}_k \leq 1$ is the k-th cluster center. To obtain the optimal K cluster centers, we introduce the binary indicator variables $r_{m,k} \in \{0, 1\}$ which denote the assigned cluster of the m-th element for $m = 1, 2, \ldots, TN_{\mathrm{s}}$ in the training dataset [9]. The binary indicator variables are given by

$$r_{m,k} = \begin{cases} 1 & \text{if } k = \arg \min\limits_{q=1,\cdots,K} \left|\bar{\gamma}_{\mathrm{t},m} - \bar{\mu}_q\right|^2, \\ 0 & \text{otherwise}, \end{cases} \tag{14}$$

where $\bar{\gamma}_{\mathrm{t},m}$ is the m-th normalized SNR in the training dataset. For the loss function, we adopt the distortion of the training phase, which is defined as

$$J_{\mathrm{t}} = \frac{1}{2TN_{\mathrm{s}}} \sum_{m=1}^{TN_{\mathrm{s}}} \sum_{k=1}^{K} r_{m,k} \left|\bar{\gamma}_{\mathrm{t},m} - \bar{\mu}_k\right|^2. \tag{15}$$

The optimal K cluster centers minimize the distortion of the training phase. We can derive the closed-form expression of the optimal k-th cluser center since the distortion in (15) is a quadratic function of $\bar{\mu}_k$ with given $r_{m,k}$. To obtain the closed-form expression of the optimal k-th cluster center, we differentiate the distortion with respect to $\bar{\mu}_k$ as

$$\frac{\partial J_{\mathrm{t}}}{\partial \bar{\mu}_k} = \frac{1}{TN_{\mathrm{s}}} \sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k} \left(\bar{\gamma}_{\mathrm{t},m} - \bar{\mu}_k\right). \tag{16}$$

Since the optimal k-th cluster center satisfies

$$\sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k} \left(\bar{\gamma}_{\mathrm{t},m} - \bar{\mu}_k^{\star}\right) = \sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k} \bar{\gamma}_{\mathrm{t},m} - \sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k} \bar{\mu}_k^{\star} = 0, \tag{17}$$

the optimal k-th cluster center is represented as

$$\bar{\mu}_k^{\star} = \frac{\sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k} \bar{\gamma}_{\mathrm{t},m}}{\sum_{m=1}^{TN_{\mathrm{s}}} r_{m,k}}. \tag{18}$$

Algorithm 1 states the pseudocode of the training phase where N_{e} indicates the number of epochs.

Algorithm 1 Training Phase for the Subcarrier Clustering

Input: $\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_{N_\mathrm{u}}$

Output: $\bar{\mu}_1, \ldots, \bar{\mu}_K$

Select $\mathcal{T} = \{t_1, .., t_\mathrm{T}\}$ randomly among N_u users
Vectorize $\left[\bar{\boldsymbol{\gamma}}_{t_1}, \ldots, \bar{\boldsymbol{\gamma}}_{t_\mathrm{T}}\right]$
Initialize K cluster centers $\bar{\mu}_1, \ldots, \bar{\mu}_K$
for $e = 1, \ldots, N_\mathrm{e}$ **do**
  for $m = 1, \ldots, TN_\mathrm{s}$ **do**
    Compute the binary indicator variable $r_{m,k}$
    Compute the optimal K cluster centers $\bar{\mu}_1^\star, \ldots, \bar{\mu}_K^\star$
  end for
  Compute the distortion J_t
  Update the K cluster centers $[\bar{\mu}_1, \ldots, \bar{\mu}_K] = [\bar{\mu}_1^\star, \ldots, \bar{\mu}_K^\star]$
end for

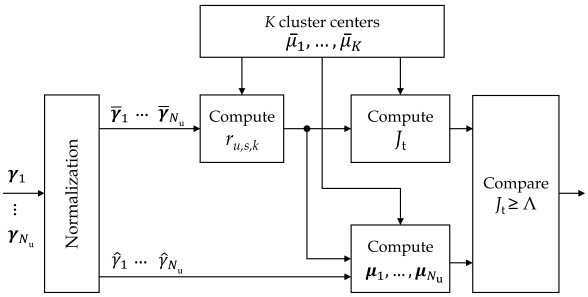

FIGURE 3. Block diagram of the test phase for the subcarrier clustering.

2) TEST PHASE FOR SUBCARRIER CLUSTERING

Fig. 3 shows the block diagram of the test phase for the subcarrier clustering. At first, we normalize the SNR of the u-th user to set the range of the input for the test phase from 0 to 1. The normalized SNR vector of the u-th user is expressed as

$$\bar{\boldsymbol{\gamma}}_u = \frac{\boldsymbol{\gamma}_u}{\hat{\gamma}_u}, \tag{19}$$

where $\hat{\gamma}_u = \max_s \gamma_{u,s}$ denotes the maximum SNR among N_s subcarriers at the u-th user. We then compute the binary indicator variables $r_{u,s,k}$ for $s = 1, 2, \ldots, N_\mathrm{s}$ as

$$r_{u,s,k} = \begin{cases} 1 & \text{if } k = \arg\min\limits_{q=1,\ldots,K} \left|\bar{\gamma}_{u,s} - \bar{\mu}_q\right|^2, \\ 0 & \text{otherwise}, \end{cases} \tag{20}$$

where $\bar{\gamma}_{u,s}$ is the normalized SNR on the s-th subcarrier of the u-th user, and $\bar{\mu}_q$ for $q = 1, 2, \ldots, K$ is the q-th cluster center obtained in the training phase. Finally, the SNR on the s-th subcarrier of the u-th user is mapped to

$$\mu_{u,k} = \hat{\gamma}_u \sum_{q=1}^{K} r_{u,s,q}\bar{\mu}_q. \tag{21}$$

As a result, we can represent the SNRs on N_s subcarriers of the u-th user $\gamma_{u,s}$ for $s = 1, 2, \ldots, N_\mathrm{s}$ to K values as

$$\boldsymbol{\mu}_u = \hat{\gamma}_u \bar{\boldsymbol{\mu}} = \hat{\gamma}_u \left[\bar{\mu}_1,\ \bar{\mu}_2,\ \ldots,\ \bar{\mu}_K\right]^\mathrm{T}. \tag{22}$$

Algorithm 2 Test Phase for the Subcarrier Clustering

Input: $\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_{N_\mathrm{u}}$

Output: $[\boldsymbol{\mu}_1, \ldots, \boldsymbol{\mu}_{N_\mathrm{u}}]$, $[r_{1,1,1}, \ldots, r_{N_\mathrm{u},N_\mathrm{s},K}]$

for $u = 1, \ldots, N_\mathrm{u}$ **do**
  Normalize $\boldsymbol{\gamma}_u$
  for $s = 1, \ldots, N_\mathrm{s}$ **do**
    for $k = 1, \ldots, K$ **do**
      Compute the binary indicator variable $r_{u,s,k}$
      Compute the assigned SNR $\mu_{u,k}$
    end for
  end for
  Compute the distortion of the u-th user J_u
end for
Compute the total distortion J_e
if $J_\mathrm{e} \geq \Lambda$ **then**
  Return to the training phase to update K cluster centers
end if

The distortion of the u-th user is defined as

$$J_u = \frac{1}{2N_\mathrm{s}} \sum_{s=1}^{N_\mathrm{s}} \sum_{k=1}^{K} r_{u,s,k} \left|\bar{\gamma}_{u,s} - \bar{\mu}_k\right|^2. \tag{23}$$

To evaluate the performance of the subcarrier clustering, we consider the total distortion of N_u users in the network as

$$J_\mathrm{e} = \frac{1}{N_\mathrm{u}} \sum_{u=1}^{N_\mathrm{u}} J_u. \tag{24}$$

If the total distortion is greater than the pre-defined threshold Λ, the subcarrier clustering returns back to the training phase to update K cluster centers. Algorithm 2 states the pseudocode of the test phase in detail.

B. POWER ALLOCATION FOR CLUSTERED SUBCARRIERS

The data rate of the u-th user after the subcarrier clustering is reformulated as

$$\tilde{R}_u = \sum_{k=1}^{K} c_{u,k} \log_2\left(1 + p_{u,k}\mu_{u,k}\right), \tag{25}$$

where

$$c_{u,k} = \sum_{s=1}^{N_\mathrm{s}} r_{u,s,k} \tag{26}$$

denotes the number of subcarriers of the u-th user in the k-th cluster. The optimal transmit power of the UAV on the k-th cluster for the u-th user is obtained by solving the following optimization problem:

$$\begin{aligned} &\max_{p_{u,k}} \sum_{u=1}^{N_\mathrm{u}} \tilde{R}_u \\ &\text{s.t.} \sum_{u=1}^{N_\mathrm{u}} \sum_{k=1}^{K} c_{u,k} p_{u,k} \leq P_\mathrm{t}, \\ &\quad \tilde{R}_u \geq R_\mathrm{t},\ u = 1, \cdots, N_\mathrm{u}, \end{aligned} \tag{27}$$

The Lagrangian of the optimization problem (27) is represented as

$$\mathcal{L}_{\mathrm{o}}\left(\{p_{u,k}\}, \lambda, \{\rho_u\}\right) = \sum_{u=1}^{N_{\mathrm{u}}} \tilde{R}_u - \lambda\left(\sum_{u=1}^{N_{\mathrm{u}}}\sum_{k=1}^{K} c_{u,k}p_{u,k} - P_{\mathrm{t}}\right) - \rho_u\left(R_{\mathrm{t}} - \tilde{R}_u\right), \quad (28)$$

where λ and ρ_u are Lagrange multipliers. The Lagrange dual function of the optimization problem (27) is given by

$$\mathcal{D}_{\mathrm{o}}\left(\lambda, \{\rho_u\}\right) = \max_{p_{u,k}} \mathcal{L}_{\mathrm{o}}\left(\{p_{u,k}\}, \lambda, \{\rho_u\}\right). \quad (29)$$

The power allocation for the clustered subcarriers (27) requires $\mathcal{O}\left(N_{\mathrm{s}} + N_{\mathrm{u}}K\right)$ computational complexity where the $\mathcal{O}\left(N_{\mathrm{s}}\right)$ term denotes the computational complexity for the subcarrier clustering. It is clear that the subcarrier clustering reduces the computational complexity of the conventional optimization problem (9) since K is much less than N_{s}.

To further reduce the computational complexity of the power allocation for clustered subcarriers, we employ the power splitting to decompose the multi-user power allocation problem into multiple single-user power allocation problems. The power splitting vector is given by

$$\boldsymbol{\alpha} = \left[\alpha_1,\ \alpha_2,\ \cdots,\ \alpha_{N_{\mathrm{u}}}\right], \quad (30)$$

where $0 \leq \alpha_u \leq 1$ denotes the power splitting factor for the u-th user with a constraint $\sum_{u=1}^{N_{\mathrm{u}}} \alpha_u = 1$. The transmit power constraint for the u-th user is then expressed as

$$P_{u,\mathrm{t}} = \alpha_u P_{\mathrm{t}} \quad (31)$$

where α_u indicates the portion of the transmit power constraint for the u-th user among the total transmit power constraint.

Applying the subcarrier clustering and the power splitting, the transmit power optimization problem for the sum-rate maximization is reformulated as

$$\begin{aligned} &\max_{p_{u,k},\alpha_u} \sum_{u=1}^{N_{\mathrm{u}}} \tilde{R}_u \\ &\text{s.t.} \sum_{u=1}^{N_{\mathrm{u}}}\sum_{k=1}^{K} c_{u,k}p_{u,k} \leq \sum_{u=1}^{N_{\mathrm{u}}} P_{u,\mathrm{t}}, \\ &\quad \sum_{u=1}^{N_{\mathrm{u}}} \alpha_u = 1, \\ &\quad \tilde{R}_u \geq R_{\mathrm{t}},\ u = 1, \cdots, N_{\mathrm{u}}, \end{aligned} \quad (32)$$

The Lagrangian of the optimization problem (32) is represented as

$$\begin{aligned} &\mathcal{L}_{\mathrm{p}}(\{p_{u,k}\}, \{\alpha_u\}, \lambda,\ \eta, \{\rho_u\}) \\ &= \sum_{u=1}^{N_{\mathrm{u}}} \tilde{R}_u \\ &\quad - \lambda\left(\sum_{u=1}^{N_{\mathrm{u}}}\sum_{k=1}^{K} c_{u,k}p_{u,k} - \sum_{u=1}^{N_{\mathrm{u}}} \alpha_u P_{\mathrm{t}}\right) \\ &\quad - \eta\left(\sum_{u=1}^{N_{\mathrm{u}}} \alpha_u - 1\right) \\ &\quad - \rho_u\left(R_{\mathrm{t}} - \tilde{R}_u\right), \end{aligned} \quad (33)$$

where λ, ρ_u, and η are Lagrange multipliers. The Lagrange dual function of the optimization problem (32) is given by

$$\mathcal{D}_{\mathrm{p}}\left(\lambda, \{\rho_u\}, \eta\right) = \max_{p_{u,k},\alpha_u} \mathcal{L}_{\mathrm{p}}\left(\{p_{u,k}\}, \{\alpha_u\}, \lambda, \eta, \{\rho_u\}\right). \quad (34)$$

Finally, we solve the Lagrange dual function (34) to obtain the optimal transmit power on the k-th cluster for the u-th user $p_{u,k}^{\star}$ and convert to near-optimal transmit power on the s-th subcarrier for the u-th user $\tilde{p}_{u,s}^{\star}$ as

$$\tilde{p}_{u,s}^{\star} = \sum_{k=1}^{K} r_{u,s,k}p_{u,k}^{\star}. \quad (35)$$

Note that (33) is equivalent to (28) with the power splitting factor constraint $\sum_{u=1}^{N_{\mathrm{u}}} \alpha_u = 1$. Therefore, we obtain near-optimal transmit power allocation of the UAV by solving (34) with two sub-Lagrange dual functions such as

$$\begin{aligned} &\mathcal{D}_{\mathrm{p}}\left(\lambda, \eta, \{\rho_u\}\right) \\ &= \max_{\alpha_u}\left[\sum_{u=1}^{N_{\mathrm{u}}} \mathcal{D}_u\left(\alpha_u, \lambda\right) - \eta\left(\sum_{u=1}^{N_{\mathrm{u}}} \alpha_u - 1\right) - \rho_u\left(R_{\mathrm{t}} - \tilde{R}_u\right)\right] \end{aligned} \quad (36)$$

and

$$\mathcal{D}_u\left(\alpha_u, \lambda\right) = \max_{p_{u,k}}\left[\tilde{R}_u - \lambda\left(\sum_{k=1}^{K} c_{u,k}p_{u,k} - \alpha_u P_{\mathrm{t}}\right)\right]. \quad (37)$$

The objective of (37) is to optimize the transmit power of the UAV which maximizes the data rate of u-th user with the transmit power constraint $\alpha_u P_{\mathrm{t}}$. The goal of (36) is to optimize the power splitting factor for users to maximize the sum-rate of the network with the constraints $\sum_{u=1}^{N_{\mathrm{u}}} \alpha_u = 1$ and $\tilde{R}_u \geq R_{\mathrm{t}}$. The computational complexity of the transmit power and the power splitting factor optimizations is $\mathcal{O}\left(K + N_{\mathrm{u}}\right)$. The two sub-Lagrange dual functions in (36) and (37) show that the transmit power optimization and the power splitting factor optimization must be performed sequentially.

1) TRANSMIT POWER OPTIMIZATION

When the power splitting factor for each user is given, the optimal transmit power for the u-th user is obtained by solving the following optimization problem:

$$\begin{aligned} \max_{p_{u,k}} & \sum_{k=1}^{K} c_{u,k} \log_2\left(1+p_{u,k}\mu_{u,k}\right) \\ \text{s.t.} & \sum_{k=1}^{K} c_{u,k}p_{u,k} \leq P_{u,\mathrm{t}}. \end{aligned} \tag{38}$$

To obtain the optimal transmit power of the UAV on the k-th cluster for the u-th user, we represent the Lagrangian of the optimization problem (38) as

$$\begin{aligned} \mathcal{L}_u\left(\left\{p_{u,k}\right\},\lambda\right) = & \sum_{k=1}^{K} c_{u,k} \log_2\left(1+p_{u,k}\mu_{u,k}\right) \\ & -\lambda\left(\sum_{k=1}^{K} c_{u,k}p_{u,k} - \alpha_u P_\mathrm{t}\right), \end{aligned} \tag{39}$$

where λ is a Lagrange multiplier. The partial differential of the Lagrangian (39) with respect to $p_{u,k}$ is represented as

$$\frac{\partial \mathcal{L}_u\left(\left\{p_{u,k}\right\},\lambda\right)}{\partial p_{u,k}} = \frac{c_{u,k}\mu_{u,k}}{\ln 2\left(1+p_{u,k}\mu_{u,k}\right)} - \lambda c_{u,k}. \tag{40}$$

It is known that the optimal transmit power $p^\star_{u,k}$ satisfies

$$\frac{c_{u,k}\mu_{u,k}}{\ln 2\left(1+p^\star_{u,k}\mu_{u,k}\right)} - \lambda c_{u,k} = 0. \tag{41}$$

Therefore, the optimal transmit power of the UAV on the k-th cluster for the u-th user is given by

$$p^\star_{u,k} = \left(\frac{1}{\lambda \ln 2} - \frac{1}{\mu_{u,k}}\right)^+, \tag{42}$$

where $(x)^+ = \max(x,0)$. The partial differential of the Lagrangian (39) with respect to λ is represented as

$$\frac{\partial \mathcal{L}_u\left(\left\{p_{u,k}\right\},\lambda\right)}{\partial \lambda} = \sum_{k=1}^{K} c_{u,k}p_{u,k} - \alpha_u P_\mathrm{t}. \tag{43}$$

Inserting the optimal transmit power $p^\star_{u,k}$ to (43), the Lagrange multiplier for the optimal transmit power satisfies

$$\sum_{k=1}^{K} c_{u,k}\left(\frac{1}{\lambda \ln 2} - \frac{1}{\mu_{u,k}}\right) - \alpha_u P_\mathrm{t} = 0. \tag{44}$$

The Lagrange multiplier for the optimal transmit power for the u-th user is represented as

$$\lambda = \frac{\sum_{k=1}^{K} c_{u,k}}{\ln 2\left(\alpha_u P_\mathrm{t} + \sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)}. \tag{45}$$

We finally obtain the optimal transmit power $p^\star_{u,k}$ by plugging in (45) into (42).

2) POWER SPLITTING FACTOR OPTIMIZATION

When the transmit power of the users is given, the optimal power splitting factor for the u-th user is obtained by solving the following optimization problem:

$$\begin{aligned} \max_{\alpha_u} & \sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K} c_{u,k} \log_2\left(1+p^\star_{u,k}\mu_{u,k}\right) \\ \text{s.t.} & \sum_{u=1}^{N_\mathrm{u}} \alpha_u = 1, \\ & \sum_{k=1}^{K} c_{u,k} \log_2\left(1+p^\star_{u,k}\mu_{u,k}\right) \geq R_\mathrm{t},\ u=1,\cdots,N_\mathrm{u}. \end{aligned} \tag{46}$$

To obtain the optimal power splitting factor, we express the Lagrangian of the optimization problem (46) as

$$\begin{aligned} & \mathcal{L}_\mathrm{p}(\{\alpha_u\},\eta,\{\rho_u\}) \\ & = \sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K} c_{u,k}\log_2\left(\frac{\left(\alpha_u P_\mathrm{t}+\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)\mu_{u,k}}{\sum_{k=1}^{K} c_{u,k}}\right) \\ & \quad -\eta\left(\sum_{u=1}^{N_\mathrm{u}}\alpha_u - 1\right) \\ & \quad -\rho_u\left(R_\mathrm{t} - \sum_{k=1}^{K} c_{u,k}\log_2\left(\frac{\left(\alpha_u P_\mathrm{t}+\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)\mu_{u,k}}{\sum_{k=1}^{K} c_{u,k}}\right)\right), \end{aligned} \tag{47}$$

where η is a Lagrange multiplier for the power splitting factor, and ρ_u is a Lagrange multiplier for the minimum rate constraint for the u-th user. The partial differential of the Lagrangian (47) with respect to α_u is represented as

$$\frac{\partial \mathcal{L}_\mathrm{p}\left(\{\alpha_u\},\eta,\{\rho_u\}\right)}{\partial \alpha_u} = \frac{\sum_{k=1}^{K} c_{u,k}(1+\rho_u)P_\mathrm{t}}{\ln 2\left(\alpha_u P_\mathrm{t} + \sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)} - \eta. \tag{48}$$

It is known that the optimal power splitting factor satisfies

$$\frac{\sum_{k=1}^{K} c_{u,k}(1+\rho_u)P_\mathrm{t}}{\ln 2\left(\alpha^\star_u P_\mathrm{t} + \sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)} - \eta = 0. \tag{49}$$

Therefore, the optimal power splitting factor for the u-th user is given by

$$\alpha^\star_u = \left(\sum_{k=1}^{K}\frac{c_{u,k}(1+\rho_u)}{\eta \ln 2} - \frac{1}{P_\mathrm{t}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)^+. \tag{50}$$

The partial differential of the Lagrangian (47) with respect to η is represented as

$$\frac{\partial \mathcal{L}_\mathrm{p}\left(\{\alpha_u\},\eta,\{\rho_u\}\right)}{\partial \eta} = \sum_{u=1}^{N_\mathrm{u}}\alpha_u - 1. \tag{51}$$

Algorithm 3 Power Allocation for Clustered Subcarriers

Input: $[\mu_{1,1}, \ldots, \mu_{N_\mathrm{u},K}]$, $[r_{1,1,1}, \ldots, r_{N_\mathrm{u},N_\mathrm{s},K}]$, P_t
Output: $p^\star_{1,1}, \ldots, p^\star_{N_u,N_s}$

```
while p_{u,k} converges do
    Compute the Lagrange multiplier λ
    for u = 1, ..., N_u do
        for k = 1, ..., K do
            Compute the optimal transmit power p*_{u,k}
        end for
    end for
    for u = 1, ..., N_u do
        Compute the normalized Lagrange multiplier ρ̄_u
        Compute the optimal power splitting factor α*_u
    end for
end while
```

Inserting the optimal power splitting factor $\alpha_u^\star$ (50) to (51), the Lagrange multiplier for the power splitting factor satisfies

$$\sum_{u=1}^{N_\mathrm{u}}\left(\sum_{k=1}^{K}\frac{c_{u,k}(1+\rho_u)}{\eta\ln 2}-\frac{1}{P_\mathrm{t}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)-1=0. \tag{52}$$

The Lagrange multiplier for the power splitting factor is represented as

$$\eta=\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}\frac{c_{u,k}(1+\rho_u)}{\ln 2}\left(1+\frac{1}{P_\mathrm{t}}\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)^{-1}. \tag{53}$$

The optimal power splitting factor $\alpha_u^\star$ can be rewritten as

$$\alpha_u^\star=\left(\bar{\rho}_u\left(1+\frac{1}{P_\mathrm{t}}\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)-\frac{1}{P_\mathrm{t}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)^{+}. \tag{54}$$

where

$$\bar{\rho}_u=\frac{\sum_{k=1}^{K}c_{u,k}(1+\rho_u)}{\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}c_{u,k}(1+\rho_u)} \tag{55}$$

denotes the normalized Lagrange multiplier for the minimum rate constraint of the u-th user. The partial differential of the Lagrangian (47) with respect to ρ_u is represented as

$$\frac{\partial\mathcal{L}_\mathrm{p}\left(\{\alpha_u\},\eta,\{\rho_u\}\right)}{\partial\rho_u}=R_\mathrm{t}-\sum_{k=1}^{K}c_{u,k}\log_2\left(\frac{\left(\alpha_uP_\mathrm{t}+\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)\mu_{u,k}}{\sum_{k=1}^{K}c_{u,k}}\right). \tag{56}$$

Inserting the optimal power splitting factor $\alpha_u^\star$ (54) to (56), the normalized Lagrange multiplier $\bar{\rho}_u$ satisfies

$$R_\mathrm{t}-\sum_{k=1}^{K}c_{u,k}\log_2\left(\bar{\rho}_u\frac{\left(P_\mathrm{t}+\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)\mu_{u,k}}{\sum_{k=1}^{K}c_{u,k}}\right)=0. \tag{57}$$

TABLE 1. Simulation Parameters.

Parameter	Value	Parameter	Value
N_s	1024	N_u	10
N_t	4	N_e	20
L	4	f_c	2.4 GHz
η_LoS	1 dB	η_NLoS	20 dB
a	9.61	b	0.16
A	100 m	d_m	300 m
K_R	5	R_t	0.1 bps/Hz
T	8	P_t	20 dBm
$\sigma^2_{u,s}$	-114 dBm	Λ	0.01

The normalized Lagrange multiplier $\bar{\rho}_u$ can be rewritten as

$$\bar{\rho}_u=2^{\frac{R_\mathrm{t}-\sum_{k=1}^{K}c_{u,k}\log_2\left(\left(P_\mathrm{t}+\sum_{u=1}^{N_\mathrm{u}}\sum_{k=1}^{K}\frac{c_{u,k}}{\mu_{u,k}}\right)\frac{\mu_{u,k}}{\sum_{k=1}^{K}c_{u,k}}\right)}{\sum_{k=1}^{K}c_{u,k}}}. \tag{58}$$

We finally obtain the optimal power splitting factor $\alpha_u^\star$ by plugging in (58) into (54). Algorithm 3 states the pseudocode of the power allocation for clustered subcarriers in detail.

The sum-rate of the UAV-enabled OFDM network with the proposed algorithm is given by

$$\tilde{R}^\star=\sum_{u=1}^{N_\mathrm{u}}\tilde{R}_u^\star=\sum_{u=1}^{N_\mathrm{u}}\sum_{s=1}^{N_\mathrm{s}}\log_2\left(1+\sum_{k=1}^{K}r_{u,s,k}p^\star_{u,k}\gamma_{u,s}\right), \tag{59}$$

where $\tilde{R}_u^\star$ is the data rate of the u-th user with the optimal transmit power and the power splitting factor.

3) CONVERGENCE AND COMPLEXITY

Since (33) is equivalent to (28) with the power splitting factor constraint $\sum_{u=1}^{N_\mathrm{u}}\alpha_u=1$, the convergence of the proposed algorithm depends on the optimal power splitting factor $\alpha_u^\star$ obtained from (54), (55), and (58). According to the definition of $\bar{\rho}_u$ in (55), the range of $\bar{\rho}_u$ should be from 0 to 1. When the u-th user cannot achieve the minimum rate constraint R_t under the total transmit power constraint P_t, $\bar{\rho}_u$ in (58) will be greater than 1, and the convergence of the proposed algorithm is not guaranteed. Thus, we conclude that the convergence of the proposed algorithm is ensured when the feasible constraints satisfying $0\leq\bar{\rho}_n\leq 1$ are given.

The computational complexity of the proposed algorithm, which consists of the subcarrier clustering and the power allocation for the clustered subcarriers with the power splitting, is given by $\mathcal{O}\left(N_\mathrm{s}+K+N_\mathrm{u}\right)$. It is clear that the proposed algorithm requires low-complexity compared to the conventional water-filling algorithm $\mathcal{O}\left(N_\mathrm{s}N_\mathrm{u}\right)$ since the number of clusters is far less than the number of subcarriers.

IV. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed algorithm. Table 1 shows the simulation parameters in detail. The users are randomly distributed within $d_\mathrm{m}=300$ m and the UAV is located at the center of the users. We consider the urban environment for the performance evaluation[2] by

[2]Although we only present the simulation results for the urban environment, we confirm that different A2G path-loss environments also give similar results to the urban environment.

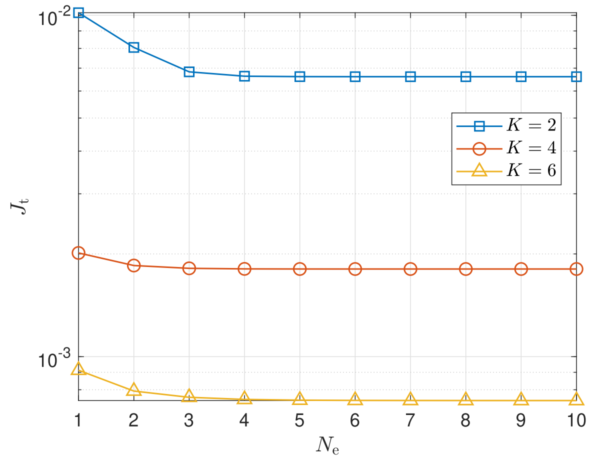

FIGURE 4. Distortion in the training phase for the subcarrier clustering.

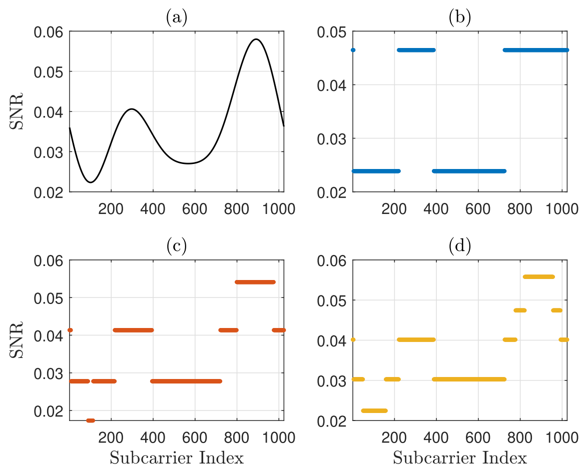

FIGURE 5. SNRs of (a) N_s subcarriers and (b) clustered subcarriers with $K = 2$, (c) $K = 4$, and (d) $K = 6$.

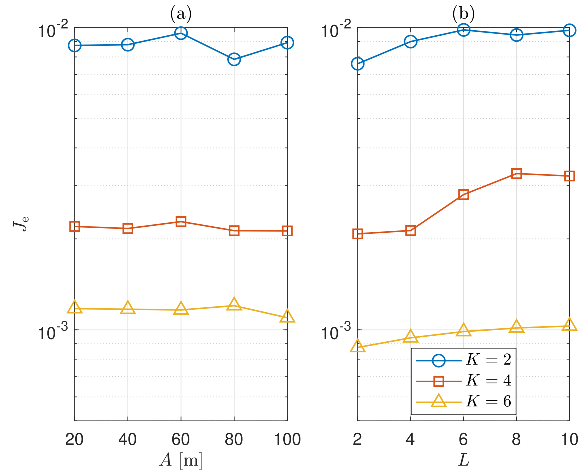

FIGURE 6. Distortion in the test phase for the subcarrier clustering as a function of (a) the altitude of the UAV and (b) the number of paths.

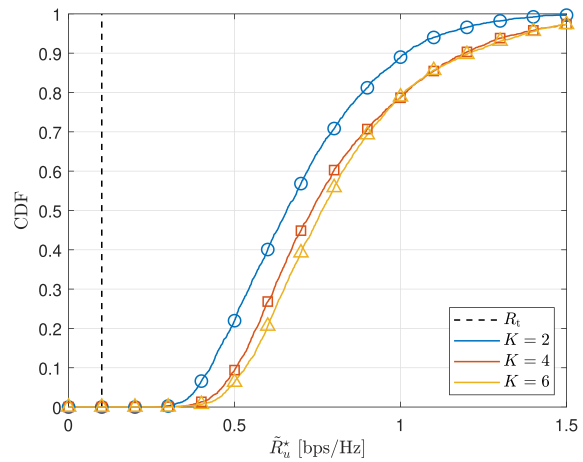

FIGURE 7. CDF of the data rate of the u-th user with the optimal transmit power and the power splitting factor.

using the parameters $\eta_{\text{LoS}} = 1$ dB, $\eta_{\text{NLoS}} = 20$ dB, $a = 9.61$, and $b = 0.16$ [38]. We compare three schemes, 'Optimal,' 'Proposed,' and 'Adjacent.' Since the most basic approach of equal power allocation does not guaranteed the minimum rate constraint for each user, the equal power allocation is excluded from the performance comparison. The 'Optimal' and 'Proposed' schemes obtain the transmit power of the UAV from the optimization problems (9) and (32), respectively. The 'Adjacent' scheme divides N_s subcarriers into K clusters of contiguous subcarriers [28], [29] and applies the power allocation for clustered subcarriers.

Fig. 4 shows the distortion as a function of epochs in the training phase for the subcarrier clustering. The distortion decreases as the number of epochs increases, indicating that the K cluster centers in (18) are well defined. It is also shown that the distortion depends on the number of clusters for the subcarrier clustering. Having more clusters minimizes the distortion but requires high computational complexity for the subcarrier clustering.

Fig. 5 shows the SNRs of N_s subcarriers and clustered subcarriers for the various number of clusters. As can be seen, the SNRs of N_s subcarriers are well represented with the K values and the SNRs of the clustered subcarriers are similar to the SNRs of the N_s subcarriers when the number of cluster is greater than $K = 4$.

Fig. 6 shows the distortion in the test phase for the subcarrier clustering for various altitude of the UAV and the number of paths. It is shown that the distortions in the test phase are similar to the distortions in the training phase even though the altitude of the UAV and the number of paths vary. We can conclude that the proposed subcarrier clustering is robust due to the normalization of the SNR. The proposed subcarrier clustering employed in the UAV-enabled OFDM network can therefore be used without any re-training for different UAV altitudes and the number of paths.

Fig. 7 plots the cumulative density function (CDF) of the data rate of the u-th user with the optimal transmit power and the power splitting factor. The figure shows that all users in the network achieve the minimum rate constraint R_t. In addition, the data rate of the u-th user increases as the number of clusters increases. We can expect that the proposed algorithm cannot guarantee the minimum rate constraint for each user with fixed transmit power when the network requires a higher data rate

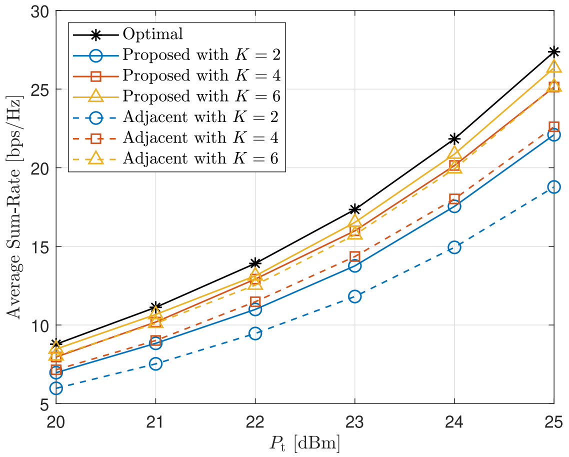

FIGURE 8. Average sum-rate of the network as a function of the total transmit power constraint of the UAV.

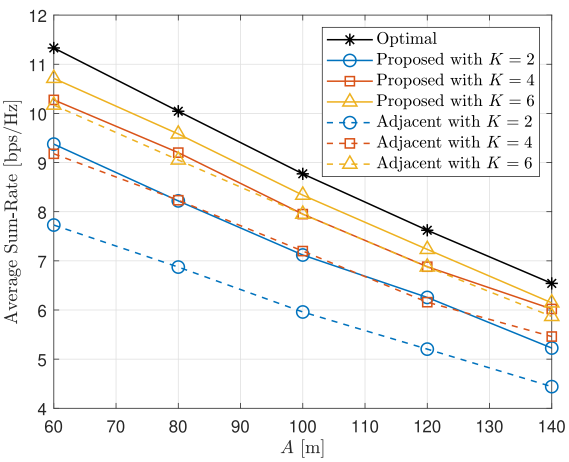

FIGURE 9. Average sum-rate of the network as a function of the UAV altitude.

constraint. Therefore, the network operator should consider the minimum rate constraint and the total transmit power simultaneously.

Fig. 8 shows the average sum-rate of the network as a function of the total transmit power constraint. The figure shows that the proposed algorithm provides a higher average sum-rate compared to the 'Adjacent' scheme with an equal number of clusters. The figure also shows that the proposed algorithm achieves near-optimal performance when the number of clusters is $K = 4$ with much less complexity. Note that the sum-rate of the network is determined by subcarriers in the high-SNR region. As shown in Fig. 5 and Fig. 6, the subcarrier clustering with $K = 4$ clusters selects the proper portion of subcarriers in the high-SNR region and maps the SNRs of N_s subcarriers to K values with less distortion. Therefore, the subcarrier clustering plays a crucial role in the proposed algorithm.

Fig. 9 shows the average sum-rate of the network as a function of the UAV altitude. We can see that the average sum-rate decreases as the altitude of the UAV increases due to the A2G path-loss. As shown in Fig. 8, the proposed algorithm provides near-optimal performance when the number of clusters is $K = 4$. The proposed algorithm also achieves near-optimal performance without re-training, despite varying altitudes of the UAV.

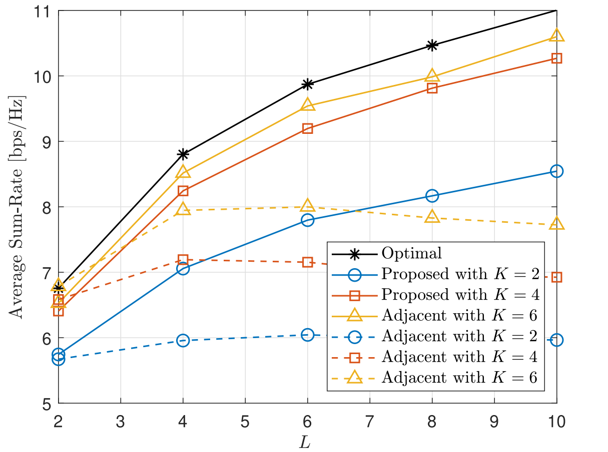

FIGURE 10. Average sum-rate of the network as a function of the number of paths.

Fig. 10 shows the average sum-rate of the network as a function of the number of paths. The figure shows that the average sum-rate of the network increases as the number of paths increases when the proposed algorithm is applied. This means that the proposed algorithm obtains multi-path diversity by properly allocating the transmit power. However, the 'Adjacent' scheme cannot achieve the multi-path diversity since the cluster with contiguous subcarriers leads to a higher distortion in the frequency selective channels. As expected, the proposed algorithm provides near-optimal performance when the number of clusters is $K = 4$.

Figs. 8 to 10 show the trade-off relation between the computational complexity and the performance loss. Therefore, we can determine the number of clusters K based on the acceptable performance loss in the network.

V. CONCLUSION

In this paper, we proposed a K-means clustering-aided power control algorithm to maximize the sum-rate of a UAV-enabled OFDM network under the total transmit power and the minimum rate constraints. The proposed algorithm is composed of the subcarrier clustering and the power splitting. The subcarrier clustering reduced the computation complexity of the power control algorithm from $\mathcal{O}(N_s N_u)$ to $\mathcal{O}(N_s + K N_u)$ by mapping the SNR of N_s subcarriers to K values. The power splitting transformed the joint N_u users power allocation problem with $\mathcal{O}(N_s + K N_u)$ complexity to N_u single-user power allocation problems with $\mathcal{O}(N_s + K + N_u)$ complexity by dividing the total transmit power constraint into the transmit power constraint for each user. Simulation results showed that the proposed algorithm with $K = 4$ clusters provides near-optimal performance, even with a large number of subcarriers $N_s = 1024$.

There are many possible extensions of our work. For example, it would be interesting to investigate trajectory planning, user clustering, and resource allocation for multi-

UAV-enabled OFDM networks taking our proposed K-means clustering-aided power control algorithm into account.

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