Abstract—To improve the poor performance of distributed operation and non-scalability of centralized operation in traditional cell-free massive MIMO, we propose a cell-free distributed collaborative (CFDC) massive multiple-input multiple-output (MIMO) system based on a novel two-layer model to take advantages of the distributed cloud-edge-end collaborative architecture in 5G (B5G) internet of things (IoT) environment to provide strong flexibility and scalability. We further utilize the proposed CFDC massive MIMO system to support the low altitude three-dimensional (3-D) coverage scenario with unmanned aerial vehicles (UAVs), while accounting for 3-D Rician channel estimation, user-centric association and different scalable receiving schemes. Since coexisted UAVs and ground users (GUEs) cause greater interference, we utilize user-centric association strategy and minimum-mean-square error (MMSE) channel state information (CSI) estimation to obtain the estimated CSI of UAVs and GUEs. Under the CFDC scenarios, scalable receiving schemes as maximum ratio combing (MRC), partial zero-forcing (P-ZF) and partial minimum-mean-square error (P-MMSE) can be performed at edge servers and the closed-form expressions for uplink spectral efficiency (SE) are derived. Based on the derived expressions, we propose an efficient power control algorithm by solving a multi-objective optimization problem (MOOP) between maximizing the average SE of UAVs and GUEs simultaneously to achieve scalability. The SE analysis under various system parameters offers numerous flexibilities for system optimization.

Index Terms—CFDC massive MIMO, 3-D coverage, UAV communication, spectral efficiency.

I. INTRODUCTION

WITH 6G puts forward higher requirements for the performance of communication systems, traditional cellular networks which have heavy performance losses and serious interference at cell edges cannot satisfy the dramatic increase of data traffic. To eliminate the cell-edge problem, the fully cooperative cell-free massive multiple-input multiple-output (MIMO) system (which also called non-cellular massive MIMO [1]–[4]) is designed by connecting all the access points (APs) together to serve the users collaboratively. However, with the increase of users and APs, the fronthaul and backhaul links expands significantly and causes large signaling overhead and time cost which is lack of practice and scalability. The other kind of cell-free massive MIMO is fully distributed cell-free massive MIMO where almost all the signal processing is operated locally at APs. The major benefit of such architecture is that new APs can be deployed easily without upgrading the computational complexity of the central processing unit (CPU), however, the performance of fully distributed system is worse due to minimal inter-AP cooperation. Traditional cell-free massive MIMO has been widely used in recent years, however bring some drawbacks. Distributed operation which processed locally at each access point (AP) achieves poor performance, while centralized operation which fully processed on the central processing unit (CPU) is lack of scalability.

To improve the non-scalability, the centralized cell-free approach is further extended to the case of a user-centric massive MIMO approach [5], [6]. In such systems, a specific cluster of APs is selected for each user and the user-centric scheme improves scalability of the whole network. [6] use the K-means++ clustering algorithm to complete AP selection. In this paper, we propose a new practical and scalable architecture called Cell-free Distributed Collaborative (CFDC) massive MIMO systems based on a partially distributed collaborative transmission architecture combines the centralized architecture with distributed architecture which processed on edge servers named spatial extension units (SEUs) to achieve a trade-off between the higher performance and scalability. By reaping the advantages from both centralized and distributed cell-free massive MIMO systems, CFDC massive MIMO can effectively improve the spectral efficiency (SE), energy efficiency (EE)
and reliable data transmission. Obviously higher performance and scalability is especially important in communications for users with high mobility such as drones.

With the higher requirements of full coverage and cost-effective in communication, unmanned aerial vehicles (UAVs), also known as drones plays a key role in low-altitude three-dimensional (3-D) coverage in recent times. Due to the low energy consumption and high autonomy, UAVs have been widely used in many fields such as photography, video, rescue, etc [9]. The main research interests of UAVs in wireless communication lies in two different fields [10]. The first one is to utilize UAVs as aerial APs and provide increasing capacity and high mobility for the wireless network to improved the coverage for disaster situations where the cellular networks are not capable [11], [12]. Compared with traditional terrestrial base stations (BSs), the aerial APs show advantages in adaptive altitude, obstacle avoidance and the higher proportion of line-of-sight (LoS) communication links [13]–[16]. The second field is to regard UAVs as aerial mobile terminals (known as cellular-connected drones), coexisted with terrestrial users, such as transport or reconnaissance drones. This new research approach concentrates on the services that the wireless networks, usually cellular networks, can bring to the UAV terminals. [17] analyzed the downlink coverage probability with the coexistence of terrestrial and aerial users in cellular networks. [18] investigated the feasibility of supporting UAVs operations based on existing cellular infrastructure. [19] integrated UAVs into the cellular network as the cellular-connected UAVs to enable the aerial users wireless communication. [20] analyzed the uplink transmission from one UAV user to BSs and investigated the inter-cell interference coordination schemes to achieve better performance. [21] measured the UAV air-to-ground propagation channel model based on a high-resolution estimation algorithm.

Compared with traditional terrestrial cellular communications, cellular-connected UAV communications obviously have different characteristics, which bring both new research challenges and opportunities. The main communication modes of UAVs can be basically divided into two categories: payload communication and control and non-payload communication (CNPC). Payload communication is to transmit data from UAVs to ground devices, such as video and image materials transmission. CNPC refers to the communication between UAVs and ground stations, such as to control the flight height and velocity of the UAVs. Due to the two modes play different roles, the requirements are completely different. CNPC usually requires higher security and lower latency to ensure real-time communication while payload communication requires higher data rate to support the heavy transmission of videos [22], [23]. These works all studied UAV communication in traditional centralized massive MIMO systems. When it comes to the payload communication, the large amounts of data puts forward higher demands for data transmission rate while the coexistence of drones and ground users (GUEs) brings more interference to reduce the rate. Therefore, we analyze the achievable rate of aerial users and terrestrial users with a Rician fading channel composed of LoS and NLoS communication links.

Recently, UAVs communication was extended to cell-free massive MIMO. [24] investigated a system consisting of a satellite and a swarm of UAVs, in which the UAVs help improve the coverage of the massive MIMO in wide areas. [25] proposed a UAVs aided cell-free network to provide coverage in a highway outside the coverage of terrestrial BSs for vehicles and approached the optimal solution for UAVs deployment based on deep reinforcement learning. These works on UAVs communication in cell-free architecture focused on the use of UAVs as BSs to improve the coverage, while the research on UAVs as users communication is less. [26] first analyzed the cellular-connected UAVs in cell-free and user-centric networks with a large number of APs deployed in a particular area. [27] analyzed the downlink SE of a cell-free massive MIMO system with hardware-impaired UAVs and GUEs under Rician fading channels. These works mainly focused on the basic performance analysis of UAVs in cell-free massive MIMO while not consider the scalability of the system structure.

To the best of our knowledge, the SE or signal-to-interference-plus-noise ratio (SINR) of coexisted UAVs and GUEs communication in uplink transmission with different receiving schemes has not been analyzed yet, not to mention under a partially distributed architecture to ensure the scalability.

This paper proposes a scalable CFDC massive MIMO system based on partially distributed architecture and investigates the SE of coexisted UAVs and GUEs low altitude 3-D coverage in CFDC massive MIMO systems with different receiving schemes. The main contributions of this paper are listed as follows:

1) We propose a CFDC massive MIMO system based on partially distributed architecture which combines the higher performance of centralized cell-free and scalability of distributed cell-free massive MIMO.

2) We analyze low altitude 3-D coverage in the proposed CFDC massive MIMO system to implement the scalability. Based on a Rician channel model, we derive the closed-form expressions for estimated channel state information (CSI) of coexisted UAV and GUE users in CFDC massive MIMO systems.

3) With the estimated CSI and user-centric association strategy, the closed-form expressions of the uplink SE of UAVs and GUEs with maximum ratio combining (MRC), partial zero-forcing (P-ZF) and partial minimum-mean-square error (P-MMSE) receiving schemes in CFDC massive MIMO are derived.

4) To jointly optimize SE of UAV and GUE users, we formulate a multi-objective optimization problem (MOOP) between two conflicting objectives of maximizing the average SE of UAVs and GUEs in CFDC massive MIMO systems. The optimal solution between these two conflicting problems is obtained by solving the MOOP with Deep Q-Network (DQN).

5) The accuracy of the derived closed-form expressions and the effectiveness of the UAVs and GUEs coexistence scenarios in CFDC massive MIMO systems are verified. Insightful conclusions are drawn from the SE analysis
The APs are used for signal transmission, caching and computing capabilities, and is responsible for enabling it to collaborate the data received and transmitted by each AP, $G_{u,k}$.

Finally, some conclusions are drawn in Section VII. Numerical result and discussions are presented in Section VI. Three receiving schemes is analyzed in Section IV. The efficient uplink channel receivers is presented in Section III. SE with SEUs and multiple APs equipped with numerous antennas on each AP, $M_{AP}$, and with the increase of the SEUs and APs, this distributed architecture can achieve unlimited scalability.

**B. Channel Model**

Considering Rician fading channel for both UAVs and GUEs, the channel from the $k$-th user to the $n$-th AP can be modeled as

$$g_{n,k} = \sqrt{\beta_{n,k}} \left( \sqrt{\frac{k_{n,k}^a}{k_{n,k}^a + 1}} \bar{h}_{n,k} + \sqrt{\frac{1}{k_{n,k}^a + 1}} h_{n,k} \right),$$

where $\beta_{n,k}$ denotes the large-scale channel fading coefficient between the $n$-th AP and the $k$-th UAV or GUE and the other part in parentheses is the small-scale fast fading. The first item $\bar{h}_{n,k}$ represents the component for LoS link, while the second item $h_{n,k}$ represents the component for NLoS link. The Rician factor $k_{n,k}^a$ is the ratio of the LoS link and NLoS link and $a \in \{UAV, \text{GUE}\}$. Owing to the altitude of UAVs, they are more likely to have stronger LoS links than GUEs, which means that the Rician factor $k_{n,k}^\text{UAV}$ of the channel between the $u$-th UAV and the $n$-th AP is likely to be larger than the Rician factor $k_{n,k}^\text{GUE}$ of the channel between the $g$-th GUE and the $n$-th AP. It is assumed that the channels of different users are uncorrelated.

Due to the user’s movement, it may affect the phase shift of the LoS component. But for convenience, for the analysis below and without losing generality, the phase shift is assumed to be accurately tracked in this system [28]. Therefore, the channel model between the $n$-th AP and the $k$-th user, without taking into account the effect of phase shift, can be built as $g_{n,k} \sim CN(\bar{g}_{n,k}, \Lambda_{n,u})$, where $\Lambda_{n,u}$ is the positive semidefinite covariance matrix of the NLoS component. Establishing the channel as a Rician channel combined with LoS link and NLoS link promotes the difficulty of derivation, but makes the analysis more practical and meaningful.

**C. Channel Estimation**

The system operates in time division duplex (TDD) mode and the TDD coherence interval is defined to be $T_p$, in which $T_p$ interval is used for uplink channel estimation. During the uplink channel estimation period, all users send uplink pilot sequences simultaneously to all APs. The pilot sequence sent by the $k$-th user is $\sqrt{T_p} \phi_k$ and are mutually orthogonal. The received pilot signal of UAVs and GUEs at the $n$-th AP can be described as

$$Y_n^{ul} = \sum_{g=1}^{G} \sqrt{T_p} P_{g}^{ul} f_{n,g} \psi_g^H + \sum_{u=1}^{U} \sqrt{T_p} q_u^{ul} g_{n,u} \phi_u^H + N_n, \quad (1)$$

where $P_{g}^{ul}$ and $q_u^{ul}$ are the pilot power of the $g$-th GUE and the $u$-th UAV, $f_{n,g}$ and $g_{n,u}$ are the channel vector of the $g$-th GUE and the $u$-th UAV, $\psi_g^H$ and $\phi_u^H$ are the pilot.
sequences of the $g$-th GUE and the $u$-th UAV and $N_n$ is the additive white Gaussian noise (AWGN).

Then the channel vector can be estimated by projecting the received signal with the pilot sequence of the $k$-th user as

$$Y_{n,k} = Y_{n,k}^{u} \frac{\varphi_k}{\sqrt{\tau_p q_k}} = g_{n,k} + \sum_{g=1}^{G} f_{n,g} y_{g}^{u} \varphi_k + \sum_{u=1}^{U} g_{n,u} y_{g}^{u} \varphi_k + \frac{N_n \varphi_k}{\sqrt{\tau_p q_k}},$$

(2)

The linear MMSE estimation [29] of the channel vector between the $k$-th UAV and the $n$-th AP $g_{n,k}$ can be given by

$$\hat{g}_{n,k} = g_{n,k} + \frac{\beta_{n,k}}{k_{n,u} + 1} \Xi_{n,k}^{-1} (Y_{n,k} - g_{n,k})$$

$$= g_{n,k} + \Lambda_{n,k} \Xi_{n,k}^{-1} \hat{f}_{n,k},$$

(3)

where

$$\Xi_{n,k} = E \left[ Y_{n,k} Y_{n,k}^H \right]$$

$$= \sum_{r \in Z_u} \vartheta_{n,r} + \sum_{j \in Z_u} \varsigma_{n,j} + \frac{\sigma^2_{NL}}{r_p q_k},$$

(4)

$Z_u$ indicate the UAV users and GUE users who share the pilot with the UAV user, $\vartheta_{n,r}$ is the covariance matrix of the channel between the $r$-th UAV and the $n$-th AP and $\varsigma_{n,j}$ is the covariance matrix of the channel between the $j$-th GUE and the $n$-th AP. The estimated channel between the $n$-th AP and the $k$-th UAV, can be built as $\hat{g}_{n,k} \sim CN(\hat{g}_{n,k}, \nu_{n,k})$, where $\nu_{n,k} = \Lambda_{n,k} \Xi_{n,k}^{-1} \hat{f}_{n,k}$. The channel estimation error $\hat{g}_{n,k} = g_{n,k} - \hat{g}_{n,k}$ is not correlated with the channel estimation $\hat{g}_{n,k}$. It can be seen that the coexistence of UAVs and GUEs brings more pilot contamination to the channel estimation, and the combination of LoS links and NLoS links makes the channel estimation more complex.

Remark 1: We propose a CFDC massive MIMO system with a novel two-layer model to take advantage of the distributed cloud-edge-end architecture in beyond 5G (B5G) internet of things (IoT) environment, and to achieve better performance and higher scalability while reducing communication overheads, which is especially important for high mobility users as UAVs. In particular, the two-layer CFDC massive MIMO system framework was designed and built to enhance the communicating and computing architecture in high mobility UAV networks.

III. UPLINK PAYLOAD DATA TRANSMISSION

A. User Association and AP Selection

In this system, to avoid excess power consumption between UAVs / GUEs and some APs which far away from the users and make little contribution to the uplink data rate in communication, a user-centric AP selection is adopted where a user is served only by a subset of APs in the system. Considering large-scale fading factors, different users select different AP series to support the effective communication. Based on user association, users related to different AP series can be assigned to reuse the pilots, which can greatly alleviates pilot overhead. A user $k$ is served by a set of APs $M_k$, and the signal compute at the SEU can be given by $\{D_k \hat{g}_{k}\}$, $D_k = \text{diag}(D_{k,1}, ..., D_{k,N})$ where $D_{k,n}$ is defined in [5] as $I_L$ for APs that serve the $k$-th user and zero otherwise.

$$D_{k,n} = \begin{cases} I_L, & n \in M_k, \\ 0, & n \notin M_k. \end{cases}$$

(5)

By using user-centric association, UAVs and GUEs connected to different APs can reuse pilot sequences, which greatly reduces pilot overhead and decreases pilot contamination. Assuming that the AP in the system is equipped with omnidirectional antennas with angle resolution capability, pilot reuse can also be achieved among UAVs and GUEs.

B. Uplink Data Transmission

In this section, the uplink payload data transmission of UAVs and GUEs in CFDC massive MIMO is studied. Since the process of uplink data transmission of UAVs and GUEs is similar, we will take UAV users as an example to show the analysis as follows.

The received signal of the $u$-th UAV at the $n$-th AP can be expressed as

$$\hat{s}_{n,u} = d_{n,u} y_{n,u}^{u} = D_{u} y_{n,u}^{u},$$

(6)

where

$$y_{n,u}^{u} = \left[ y_{n,u}^{u} \right]_{1,1}^{T} = \sum_{u=1}^{G} g_{u,s_u} + \sum_{g=1}^{U} f_{g} x_{g} + n, \quad (7)$$

where

$$n = \mathbb{C} \mathbb{N}(0, \sigma_{\mathbb{N}}^{2} I_{NL})$$

and $s_u = [s_{1,u}, ..., s_{N,u}]^T$ are the data received from GUEs and UAVs.

The received signal at the SEU can be processed as

$$\hat{s}_{u} = \varphi u_{u} D_{u} \left( \sum_{r=1}^{L} g_{r,s_r} + \sum_{g=1}^{G} f_{g} x_{g} + n_{u} \right)$$

$$= \varphi u_{u} D_{u} \tilde{g}_{u,s_u} + \varphi u_{u} D_{u} \tilde{g}_{u,s_u} + \sum_{r=1}^{L} \varphi u_{u} D_{u} g_{r,s_r}$$

$$+ \sum_{g=1}^{G} \varphi u_{u} D_{u} f_{g} x_{g} + \varphi u_{u} D_{u} n_{u},$$

(8)

where $\varphi = [\varphi_1, \varphi_2, ..., \varphi_N]$ represents the connection matrix between the SEUs and APs which is usually wired, $\varphi_n = [\varphi_{1,n}, \varphi_{2,n}, ..., \varphi_{M,n}]^T$. $V = [v_1, v_2, ..., v_U]^T$ is the receiving matrix of UAVs and $W = [w_1, w_2, ..., w_C]^T$ is for GUEs.

The received signal at the CPU is a weighted sum which can be expressed as

$$\tilde{S}_{u} = \xi \hat{s}_{u},$$

(9)

where $\xi = [\xi_1, \xi_2, ..., \xi_M]$ represents the weighted sum matrix of the SEUs computing at a CPU.

In this architecture, cooperative signal processing between APs is implemented on the SEU to guarantee the scalability of the system and collaborate the SEUs by CPU to improve the performance of the system.
C. Uplink Channel Receiver

After obtaining the uplink CSI with the uplink pilot sequences, the SEU can process the received signals with different receiving schemes based on the acquired CSI. We utilize scalable receiving schemes in which the computational complexity per user is independent of the number of users and APs.

With the simplest scheme MRC, we have

\[ \mathbf{v}^{\text{MRC}}_u = \mathbf{D}_u \hat{\mathbf{g}}_u. \]  

(10)

This scheme maximize the power of the desired signal while ignoring interference and estimation errors. Since the combing vector is equal to the MMSE channel estimation of the selected APs for UAV user \( u \), the solution enjoys low complexity.

By performing P-ZF scheme with a interference zero-forcing at SEU, we have

\[ \mathbf{v}^{\text{PZF}}_u = \mathbf{D}_u \hat{\mathbf{g}}_u \left( \sum_{i \in S_u} q_i \hat{\mathbf{g}}_i^H \mathbf{D}_u \hat{\mathbf{g}}_i \right)^{-1}, \]  

(11)

where \( S_u = \{ r : \mathbf{D}_u \mathbf{D}_r \neq 0_{N \times N_L} \} \) denotes the user set connected to partly the same APs as UAV \( u \).

Different from traditional ZF scheme which is not scalable in cell-free massive MIMO, the P-ZF scheme is completed at SEUs and only affected by the related users that are connected to partially the same APs.

With a P-MMSE combining scheme, we have

\[ \mathbf{v}^{\text{PMSE}}_u = q_u \mathbf{D}_u \hat{\mathbf{g}}_u \left( \sum_{i \in S_u} q_i \hat{\mathbf{g}}_i^H \mathbf{D}_u \hat{\mathbf{g}}_i + \mathbf{Z}_{S_u} + \sigma_w^2 \mathbf{I}_{N_L} \right)^{-1}, \]  

(12)

where \( \mathbf{Z}_{S_u} = \sum_{r \in S_u} q_r \mathbf{D}_r \tilde{\mathbf{z}}_r + \sum_{g \in S_u} p_g \hat{\mathbf{D}}_g \tilde{\mathbf{g}}_g, \tilde{\mathbf{z}}_r = \Lambda_r - \Lambda_r \Xi_r \tilde{\mathbf{z}}, \tilde{\mathbf{g}}_g = \Pi_g - \Lambda_r \Xi_r \tilde{\mathbf{g}}_g, \Lambda_r = [\Lambda_{1,r}, ..., \Lambda_{N,r}]^T, \Pi_g = [\Pi_{1,g}, ..., \Pi_{N,g}]^T \) are the covariance matrix of NLoS link of UAVs and GUEs.

Owing to the distributed APs in the CFDC system, it is reasonable to assume that the interference affecting a particular user is mainly caused by a small fraction of the other users, which are located near the user. Based on this phenomenon, the computational complexity of the P-MMSE receiving scheme can be greatly reduced.

The corresponding receiving vectors of GUEs \( \mathbf{w}_g \) can be obtained by replacing \( q_u \mathbf{D}_u \hat{\mathbf{g}}_u \) and \( S_u \) with the uplink power of GUE \( p_g \), the selection matrix of GUE \( \mathbf{C}_g \), the estimated channel of GUE \( \mathbf{f}_g, \mathbf{g}_n \sim \mathcal{CN} (\mathbf{0}, \mathbf{I}) \) and the user set connected to partly the same APs as GUE \( g \) \( R_g \).

Remark 2: By improving the traditional receiving method into a partially distributed receiving method with scalability, although the ability of interference elimination may be slightly reduced, the resource overhead is greatly alleviated and the computational complexity is reduced.

IV. UPLINK SPECTRAL EFFICIENCY ANALYSIS

In this section, the uplink achievable SE of both UAVs and GUEs is analyzed with different receiving schemes in CFDC massive MIMO system. By using the standard capacity bounding theory described in [30], [31] can be rewritten as [13]

\[ \hat{\mathbf{S}}_u = \xi \phi^H \mathbf{D}_u \left( \sum_{r=1}^{U} \hat{\mathbf{g}}_r \mathbf{s}_r + \sum_{g=1}^{G} \xi \phi^H \mathbf{D}_g \mathbf{x}_g + \mathbf{n}_u \right) = \xi \phi^H \mathbf{D}_u \mathbf{s}_u + \xi \phi^H \mathbf{D}_u \mathbf{x}_u + \mathbf{I}_u \]

(13)

where \( \mathbf{I}_u = \sum_{r \neq u}^{U} \xi \phi^H \mathbf{D}_u \mathbf{s}_r + \sum_{g=1}^{G} \xi \phi^H \mathbf{D}_u \mathbf{x}_g \) denotes the interference from other uplink terminals and noise. Based on [13], the instantaneous effective SINR of UAVs and GUEs can be obtained with [14] and [15].

\[ \text{SINR}_{\text{UAV},u} = \frac{q_u^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{D}_u \hat{\mathbf{g}}_u|^2 \right]}{\Gamma_{1,u} - q_u^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{D}_u \hat{\mathbf{g}}_u|^2 \right] + \Gamma_{Z,u} + \Gamma_{N,u}}, \]

(14)

where \( \Gamma_{1,u} = \sum_{r=1}^{U} q_r^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{D}_r \hat{\mathbf{g}}_r|^2 \right] + \sum_{g=1}^{G} q_g^2 \mathbb{E} \left[ \xi \phi^H \mathbf{D}_g \hat{\mathbf{f}}_g \right] , \) \( \Gamma_{Z,u} = \xi \phi^H \mathbf{Z}_u \hat{\mathbf{v}}_u , \) \( \Gamma_{N,u} = \sigma_w^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{D}_u \hat{\mathbf{v}}_u|^2 \right] . \)

\[ \text{SINR}_{\text{GUE},u} = \frac{p_g^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{C}_g \hat{\mathbf{f}}_g|^2 \right]}{\Psi_{1,g} - p_g^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{C}_g \hat{\mathbf{f}}_g|^2 \right] + \Psi_{N,g}}, \]

(15)

where \( \Psi_{1,g} = \sum_{j=1}^{G} p_j \mathbb{E} \left[ |\xi \phi^H \mathbf{C}_g \hat{\mathbf{f}}_j|^2 \right] + \sum_{j=1}^{G} p_j \mathbb{E} \left[ \xi \phi^H \mathbf{C}_g \hat{\mathbf{f}}_j \right] \), \( \Psi_{N,g} = \sigma_w^2 \mathbb{E} \left[ |\xi \phi^H \mathbf{C}_g \hat{\mathbf{v}}_u|^2 \right] \).

\[ \text{SE} = \left( 1 - \frac{\tau}{T} \right) \log_2 (1 + \text{SINR}), \]

(16)

Each item can be solved with different receiving schemes obtained in the previous section.

Theorem 1: By substituting the MRC vector into [14], the closed-form expressions of achievable SINR of UAVs with MRC receiver can be obtained with [17].
where interference from the GUEs share the same pilot sequence. Furthermore, the traditional centralized and distributed cell-free massive MIMO can be considered as special cases of the CFDC massive MIMO system.

Proof: Please refer to Appendix B.

Theorem 2: The closed-form expressions of achievable SINR of UAVs and GUEs with P-ZF receiver can be given by

\[
\text{SINR}_{\text{UL},k}^{\text{P-ZF}} = \left( \sum_{i \in S_k} \frac{\sum_{n=1}^N \xi_m \varphi_m,n \Theta_{\text{UL},k}}{\sum_{n=1}^N (Y_{u_k} + \sigma^2_{ul})} \right)^2,
\]

where \( Y_{u_k} = \sum_{i \in S_k} q_{ul}^i \omega_i + \sum_{n \in S_k} p_{ul}^n \Theta_{\text{UL},k} \).

Proof: Please refer to Appendix B.

Theorem 3: The closed-form expressions of achievable SINR of UAVs and GUEs with P-MMSE receiver can be given by

\[
\text{SINR}_{\text{UL},k}^{\text{P-MMSE}} = \frac{\sum_{m=1}^M \xi_m \varphi_m,n \Theta_{\text{UL},k}^{\text{MMSE}(0)}}{\sum_{n=1}^N \Theta_{\text{UL},k}^{\text{MMSE}(1)} + \Theta_{\text{UL},k}^{\text{MMSE}(1)} + \sigma^2_{ul} I_{NL}},
\]

where \( \Theta_{\text{UL},k}^{\text{MMSE}(0)} = q_{ul}^i d_{n,u} \omega_{n,u} \Theta_{\text{UL},k} \), \( \Theta_{\text{UL},k}^{\text{MMSE}(1)} = Z_{S_k} \Theta_{\text{UL},k}^{\text{MMSE}(1)} = T_{R_g} \).

Proof: Please refer to Appendix C.

Remark 3: In CFDC massive MIMO scenarios, due to the collaboration between SEUs, the SE of UAVs and GUEs can be greatly promoted than distributed operation and the scalability can be better than fully coordinated scenarios. Besides, since the closed-form expressions we derived only rely on large-scale fading parameters which change much slower than small-scale parameters, this is much highly practical. Furthermore, the traditional centralized and distributed cell-free massive MIMO can be considered as special cases of the CFDC massive MIMO system.

V. JOINT SPECTRAL EFFICIENCY OPTIMIZATION OF POWER ALLOCATION

As shown in the derived closed-form expressions of achievable SE (also SINR) \(^1\) \(^2\) \(^3\) \(^4\) \(^5\) \(^6\) and \(^7\), the SE of both UAVs and GUEs can be influenced by the uplink transmitted power of UAVs and GUEs. However, due to the cross-link interference between UAVs and GUEs, the SE of UAVs and GUES are conflicting with each other, i.e. with the increase of the uplink transmitted power of UAVs, the SE of GUES will decrease and vice versa, which means that UAV and GUE users cannot achieve the highest SE simultaneously. Therefore, the power control of uplink transmission is important for UAVs and GUEs to achieve considerable SE. As a result, it is necessary to obtain a tradeoff between UAVs and GUEs. In this section, a multi-objective optimization problem (MOOP) is formulated and feasible power control algorithm is proposed to realize joint optimization of the SE of UAVs and GUEs with different receiving schemes.

A. Problem Formulation

The first optimization objective is to maximize the average uplink achievable SE of UAVs, which can be described as

\[
P_1 : \max_P \sum_{u=1}^U \text{SE}_{\text{UL},u}^{\text{pre}} / U,
\]

\( s.t. \) \( \forall u \in U \)

\( C1 : \text{SE}_{\text{UL},u}^{\text{pre}} \geq \text{SE}_{\text{UL},u}^{\text{pre,min}}, \forall u \in U \) \( \quad \) \( (21) \)

\( C2 : \text{SE}_{\text{GUE},g}^{\text{pre}} \geq \text{SE}_{\text{GUE},g}^{\text{pre,min}}, \forall g \in G \) \( \quad \) \( (22) \)

\( C3 : p_{ul}^g \leq P_{ul}^{\text{max}}, \forall u \in U \) \quad \( (23) \)

\( C4 : q_{ul}^g \leq P_{ul}^{\text{max}}, \forall g \in G \) \quad \( (24) \)

where \( P = \{ p_{ul}^q, q_{ul}^q \} \), \( p_{ul}^q = [p_{ul,1}, \ldots, p_{ul,n}] \) and \( q_{ul}^q = [q_{ul,1}, \ldots, q_{ul,n}] \) and pre refers to different receiving schemes. C1 and C2 are the ergodic uplink QoS constraints, where \( \text{SE}_{\text{UL},u}^{\text{pre-min}} > 0 \) and \( \text{SE}_{\text{GUE},g}^{\text{pre-min}} > 0 \) are the required minimum SE of UAVs and GUEs. C3 and C4 are the uplink power constraints where \( P_{ul}^{\text{max}} \) and \( P_{ul}^{\text{max}} \) are the upper limits of the uplink transmitted power per UAV and GUE.

The second optimization objective is to maximize the average uplink achievable SE of GUES, which can be described as

\[
P_2 : \max_P \sum_{g=1}^G \text{SE}_{\text{GUE},g}^{\text{pre}} / G,
\]

\( s.t. \) \( C1 \sim C5. \)

For the non-convexity of \( \text{SE}_{\text{UL},u}^{\text{pre}} \) and \( \text{SE}_{\text{GUE},g}^{\text{pre}} \), it is very difficult to find the maximum value. Since the two problem of the maximization of average achievable SE of UAV \( P_1 \) and GUE \( P_2 \) are conflicting, we propose a MOOP to investigate the trade-off between these two problems. Where \( F \) is the optimal vector containing the objective functions \( P_1 \) and \( P_2 \).
The MOOP aims to maximize the average SE of UAVs and GUEs simultaneously.

$$\max_{\mathbf{P}} \quad \mathbf{F} = [\mathcal{P}1, \mathcal{P}2]^T,$$

s.t. \( C1 - C5, \)

**Remark 4:** It is noteworthy that since the two objectives in the proposed MOOP is conflicting, it cannot be transformed into multiple single-objective optimization by giving one Pareto-optimal solution at a run, for these kind of methods may obtain different solutions at different runs and not give a joint optimal solution. Moreover, the two problems in the MOOP are both non-convex, which means that it is also difficult to solve them by convex optimization methods. The optimal transmit power of both UAVs and GUEs are complex and difficult to estimate.

### B. Solutions by DQN

We apply a feasible power control scheme based on the DQN algorithm to accelerate the learning speed and address the MOOP more efficiently. In the abstract, when it comes to reinforcement learning, the agent learns the optimal policy \( \pi \) for decision-making. The DQN proposed by Google Deepmind \([32]\) replace the table in conventional Q-learning with neural network to approximate the state-action function. The training data of DQN is generated from the interaction with environment. The system state is presented as \( s(t) \) and the action is presented as \( a(t) \) at time slot \( t \). The current state is judged by observing the feedback from the environment and determines its action. A convolutional neural network (CNN) is required in DQN for the state-action space are so big that the traditional Q-table cannot satisfy.

In our proposed algorithm, the state \( s(t) \) is defined as

$$s(t) \triangleq P(t),$$

where \( P(t) \) represents the power control vector in step \( t \). The action \( a(t) \) is defined as

$$a(t) \triangleq \tilde{P}(t),$$

where \( \tilde{P}(t) \) represents the change of uplink transmit power in step \( t \) and only 0.1W can be changed per step. The reward \( r(t) \) is defined as

$$r(t) \triangleq \mathcal{P}1(p) + \gamma \ast \mathcal{P}2(p) - \tilde{r},$$

where \( \mathcal{P}1(p) \) in \((20)\) denotes the average SE of UAVs, \( \mathcal{P}2(p) \) in \((26)\) denotes the average SE of GUEs, \( \gamma \) is a regular coefficient to ensure the convergence of the network and \( \tilde{r} \) is a constant related to the sum of the average SE of UAVs and GUEs.

Based on state-action value Q and epsilon greedy scheme, the action \( a(t) \) of the highest Q-value will be selected with a fixed probability \( \varepsilon_t \). Otherwise, in case there is greater state which has not been explored, a random action will be taken. After that, the reward \( r(t) \) can be got and the next state \( s(t+1) \) can be reached. With a combined transition containing the above variables \( d(t) = [s(t), a(t), r(t), s(t+1)] \) stored into memory, a minibatch is uniformly sampled to train the CNN. At each step, the current system state \( s(t) \) is input into the CNN and then the output from CNN \( Q(s(t), a(t)) \) is obtained. The parameters of the CNN are optimized by minimizing the squared error loss as following

$$L(t) = \left(r(t) + \ell \max_{a' \in A} Q(s', a') - Q(s(t), a(t))\right)^2,$$

where \( r(t) \) is the reward of action \( a(t) \) in step \( t \), \( \ell \) denotes the discount parameter, \( \max_{a' \in A} Q(s', a') \) denotes the maximum Q-value of the next state \( s' \). A is the action set and \( Q(s(t), a(t)) \) denotes the Q-value of the selected action \( a(t) \) in state \( s(t) \).

The complexity of solving the MOOP based on DQN consists of the forward propagation and backward propagation of deep neural network mainly depends on the complexity of matrix multiplication. Therefore, the complexity of the proposed algorithm can be presented by \( O\left(2 \left(K n_1 + 2K n_{x-1} + \sum_{l=2}^{L} n_l n_1\right) s k\right) \), where \( K = 10 \) denotes the number of users and the number of nodes of input layer, \( 2K \) denotes the total number actions and the nodes of output layer, \( X = 2 \) denotes the number of network layers, \( n_l \) denote the number of nodes of \( l \)-th layer, \( s \) is the size of mini-batch and \( t \) is the number of iterations. The power control algorithm based on DQN is shown in Algorithm 1.

**Algorithm 1 Power Control Algorithm Based on DQN**

Initialize the state \( s(0) \) and the parameters of neural network

while \( t < t_{\text{max}} \) do
- Select action \( a(t) \) with \( \varepsilon \)-greedy strategy
- Get the state-action Q-values
- Observe the next state \( s' \)
- Calculate the reward \( r(t) \) of action \( a(t) \) in step \( t \)
- Store the transition \( d(t) \) into memory for neural network optimization
- \( t = t + 1 \)
end while

Output the optimal state \( s_{\text{max}} \) with the greatest reward

## VI. NUMERICAL RESULTS

In this section, we use Monte Carlo simulation to verify the closed-form expression derived. With the numerical result, we analyze the uplink SE of UAVs and GUEs under different receiving schemes.

### A. Simulation Parameters

As it is shown in Fig. 2 in simulation, assuming in a cylindrical area, there are 2 SEUs, 6 APs evenly distributed and 10 UAV user terminals and 10 ground user terminals randomly distributed. The path loss for UAVs and GUEs are defined as \( \beta_{u.g} = bd^{-a_u} \) and \( \alpha_{n.g} = bd^{-a_g} \) respectively, where \( d \) is the distance between APs and users, \( a \) is path loss index and \( b \) is the median of the average path gain at the reference distance \( d = 1 \text{ km} \).
Fig. 2. Simulation system configure.

Table I
SIMULATION PARAMETER SETTINGS

| Item                     | Number                  |
|--------------------------|-------------------------|
| SEU distribution         | Radius: 300m, Height: 3m |
| AP distribution          | Radius: 500m, Height: 10m |
| UAV distribution         | Horizontal: uniform, Vertical: uniform between 10m and 100m |
| GUE distribution         | Horizontal: uniform, Vertical: 1.5m |
| Path loss index $\alpha$ | 3.7                     |
| Uplink power $p_{ul}$    | [2w, 3w]                |
| Noise power              | -174 dBm                |
| Coherence time $T$       | 196                     |

In this section, a uniform linear array with omnidirectional antennas is assumed to be employed to all APs, and the LoS component $\overline{h}_{n,k}$ can be modeled as

$$\overline{h}_{n,k} = \begin{bmatrix} 1, e^{-j2\pi d \sin(\theta_{n,k})}, \ldots, e^{-j2\pi(L-1) \sin(\theta_{n,k})} \end{bmatrix}^T,$$  

(34)

where the antenna spacing coefficient factor is defined as $d = 0.5$ and $\theta_{n,k}$ is the arrival angle from the $k$-th user to the $n$-th AP.

According to the Rician channel model in [28], the possibility of having a LoS link within a channel mainly depends on the distance $d_{n,k}$ between the $k$-th user and the $n$-th AP. For the difference between ground-to-ground channels and air-to-ground channels, we define the possibility of owning a LoS link component as

$$\text{Pos} (\text{LoS}_{\text{air-ground}}) = 1 - \frac{d_{n,k}}{1000}, 0 < d_{n,k} < 1000\text{m}$$

$$\text{Pos} (\text{LoS}_{\text{ground-ground}}) = 1 - \frac{d_{n,k}}{300}, 0 < d_{n,k} < 300\text{m}$$

(35)

Otherwise, assume that is impossible to have a LoS link component. With the possibility of LoS links, the Rician factor between the $k$-th user and the $n$-th AP can be calculated as

$$k_{n,k} = \begin{cases} 10^{1.3-0.003d_{n,k}}, & \text{if LoS component exists} \\ 0, & \text{if LoS component does not exist} \end{cases}$$

(36)

Based on the above channel model parameters, a specific Rician fading channel model between the $n$-th AP and the $k$-th user can be obtained and it is used in all the following simulations. The other specific parameters are shown in Table I.

B. Simulation Result Analysis

Fig. 3 verifies the theoretical and simulation values of the uplink achievable rate of UAVs and GUEs with MRC, P-ZF and P-MMSE receiver against the number of antennas per AP. It is verified that the closed-form expressions (17), (18) and (19) are accurate while the simulation results agree well with the theoretical results we deduced.

With the collaboration between SEUs and the closer distance between APs and users due to dispersed distribution in
CFDC massive MIMO scenarios, both the UAVs and GUEs are less susceptible than traditional massive MIMO by the location of APs. By using P-ZF and P-MMSE receivers in CFDC massive MIMO systems, the SE of both UAVs and GUEs is effectively improved with high scalability.

Fig. 4 illustrates the comparison of the cumulative distribution function (CDF) of the SE of UAVs and GUEs with MRC, P-ZF and P-MMSE receiver between CFDC massive MIMO and fully coordinated massive MIMO under the same parameters. To guarantee the fairness of the comparison, the position of users, the number of APs and the other parameters are set exactly the same. The number of antennas per AP is set to 50. As shown in Fig. 4(a) and Fig. 4(b), the achievable SE of UAVs and GUEs in CFDC massive MIMO is approaching that in fully coordinated massive MIMO systems. However, in unscalable fully coordinated massive MIMO, all APs need to send data and CSI to a CPU which carries out those tasks with heavy fronthaul signaling. Due to the collaboration between SEUs, CFDC massive MIMO can achieving near-optimal performance with better scalability and feasibility, especially in low-altitude 3-D coverage scenarios with fragmented UAV users and large amounts of data.

Fig. 5 illustrates the effects of different numbers of serving APs on SE. One AP, three APs, and five APs are analyzed for simulation, which respectively indicates the scenarios of very few APs, moderate APs, and a lot of APs. It can be seen from the figure that with only one AP, the performance of both UAVs and GUEs are worse, especially with P-ZF and P-MMSE receivers, while in the cases of three APs and five APs, the performance of users are much better and relatively closer. This is because when each user is served by five APs, the interference from other users associated with partly the same APs will also be greater, which also affects the performance of the user. As a result, the moderate number of APs selected for each user can effectively achieve better performance, especially when the number of users is very large.
Uplink Transmission Power of UAVs

Fig. 6. Spectral efficiency against uplink transmission power of UAVs

Fig. 7. Power control optimization based on DQN

Fig. 8. Sum achievable rate comparison based on DQN and fixed maximal value

UAVs and 5 GUEs to the CNN and the other parameters are set consistent with Table I. Considering the longer uplink transmission distance and higher power consumption of UAVs, the upper boundary of uplink transmitted power of UAVs and GUEs are respectively set to 10W and 5W. Since the MOOP consists of two conflicting objectives, the achievable rate of UAVs and GUEs cannot achieve the highest value simultaneously. As shown in Fig. 8, the fixed value is set to the maximum of the power constraints and it can been seen that the sum achievable rate of UAVs and GUEs is generally to be lower than that based on DQN algorithm. Due to the interference between UAVs and GUEs, the transmitted power cannot be set to the maximum blindly. With DQN, the neural network help us to choose the optimal uplink power combination of UAVs and GUEs under a series of constraints and the MOOP is solved successfully.

VII. CONCLUSION

In this paper, we proposed a novel two-layer model called CFDC massive MIMO systems to achieve better performance and scalability and studied the low altitude 3-D coverage scenario in CFDC massive MIMO systems. With the estimated CSI based on Rician channel model and the user-centric association strategy, we deduced the closed-form expression of uplink SE of UAVs and GUEs with MRC, P-ZF and P-MMSE receiving schemes in CFDC massive MIMO. With the derived expressions, we proposed a MOOP between two conflicting objectives, the maximum of the average SE of UAVs and GUEs under several constraints, and solved the MOOP by DQN algorithm. We verified the derived closed-form expressions by Monte Carlo simulation and compared the CFDC massive MIMO system with fully coordinated cell-free massive MIMO system under the same parameters to show that CFDC massive MIMO system can also perform well and provide scalability. Besides, it was verified that the user-centric association can effectively achieve higher SE with lower power consumption. The effects of uplink transmitted power of UAV on the rate of both GUEs and UAVs were
analyzed. The optimal solution of the MOOP obtained with DQN under various constraints offered numerous flexibilities for system optimization.

**APPENDIX A**

**PROOF OF THEOREM 1**

We first calculate the needed signal for UAV users (UAVs as an example). By substituting the MRC receiving vector into the item $\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_u \right]$, we have

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_u \right] = \mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_u \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right].
$$

(A1)

Then, for the denominator part $\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_r \right]$, we have

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_r \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(A2)

When users $r$ and $u$ share a pilot, we can obtain

$$
\mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_r \right] = \sum_{n=1}^{N} \Lambda_{n,u} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right] \Lambda_{n,r} + \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_r \right].
$$

(A3)

When users $r$ and $u$ do not share a pilot, we can obtain

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{g}_r \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_r \right],
$$

(A4)

For the denominator part $\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{f}_u \right]$, we have

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{f}_u \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(A5)

For the denominator part $\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{v}_u \right]$, we have

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{v}_u \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(A6)

For the denominator part $\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{v}_u \right]$, we have

$$
\mathbb{E} \left[ \mathbf{\varphi}^H \mathbf{D}_u \mathbf{v}_u \right] = \sum_{m=1}^{M} \xi_m \sum_{n=1}^{N} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(A7)

The conclusion can be proved by substituting the values of the above fractions into (13).

For GUEs, we can calculate the signal for users similarly, by substituting the receiving vector into (15).

**APPENDIX B**

**PROOF OF THEOREM 2**

By substituting the P-ZF vector of UAVs (11) into (13), the received signal can be rewritten as

$$
\mathbf{\varphi} \left( \sum_{i \in S_u} \mathbf{\tilde{g}}_i^H \mathbf{D}_u \mathbf{g}_i \right)^{-1} \mathbf{D}_u \mathbf{g}_u \mathbf{v}_u
$$

(B1)

where $\mathbf{v}_u = \sum_{r \neq u} \mathbf{D}_u \mathbf{g}_r \mathbf{v}_r + \sum_{g=1}^{G} \mathbf{D}_u \mathbf{f}_g \mathbf{x}_g + \mathbf{n}_u$.

Then the instantaneous effective SINR of UAVs can be given by (B2), where $\mathbf{\hat{S}}_u = \mathbf{Z}_{u} + \sigma_{d_{u}}^2 \mathbf{I}_{NL}$ is the interference plus noise covariance matrix to UAV $u$.

Similarly, the effective SINR of GUEs can be given by (B3), where $\mathbf{\hat{S}}_g = \mathbf{T}_g + \sigma_{d_{g}}^2 \mathbf{I}_{NL}$ is the interference plus noise covariance matrix to GUE $g$ with

$$
\mathbb{E} \left[ \mathbf{\varphi} \mathbf{P}_u^H \mathbf{Z}_{S_u} \mathbf{v}_u \mathbf{v}_u^H \mathbf{P}_u \right] = \sum_{i \in S_u} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(B4)

where $\mathbf{P}_u = \sum_{r \in S_u} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right] + \sum_{g \in S_u} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],

$$
\mathbb{E} \left[ \mathbf{\varphi} \mathbf{P}_u^H \mathbf{v}_u \mathbf{v}_u^H \mathbf{P}_u \right] = \sum_{i \in S_u} \varphi_{m,n} \mathbb{E} \left[ \mathbf{g}_u^H \mathbf{g}_u \right],
$$

(B5)
the received signal can be rewritten as

$$\text{SINR}_{\text{UAV},u}^{\text{ul}} = \frac{\xi \varphi \left( \sum_{i \in S_u} \hat{g}_i^H \mathbf{D}_u \hat{g}_i \right)^{-1} \xi \varphi \mathbf{D}_u}{\xi \varphi \left( \sum_{i \in S_u} \hat{g}_i^H \left( \hat{S}_u \otimes I_{NL} \right) \mathbf{D}_u \hat{g}_i \right)^{-1} \xi \varphi \mathbf{H}_u},$$  \hspace{1cm} (B2)

$$\text{SINR}_{\text{GUE},g}^{\text{ul}} = \frac{\xi \varphi \mathbf{C}_g}{\xi \varphi \left( \sum_{j \in R_g} \hat{f}_j^H \mathbf{C}_g \hat{f}_j \right)^{-1} \xi \varphi \mathbf{C}_g} \left( \sum_{j \in R_g} \hat{f}_j^H \mathbf{C}_g \hat{f}_j \right)^{-1} \varphi \mathbf{H}_u,$$  \hspace{1cm} (B3)

In the instantaneous effective SINR of GUEs (B3), each item in denominator can be given by

$$\mathbb{E} \left[ \left\| \xi \varphi \mathbf{w}_g \mathbf{H} \right\|^2 \right] = \sum_{m=1}^{M} \xi_m^2 \sum_{n=1}^{N} \varphi_{m,n}^2 \mathbb{E} \left[ \left( \sum_{j \in R_g} \mathbf{C}_g \hat{f}_j \mathbf{C}_g \right)^{-1} \right] \right]$$

$$= \sum_{m=1}^{M} \xi_m^2 \sum_{n=1}^{N} \varphi_{m,n}^2 \mathbb{E} \left[ \sum_{j \in R_g} \mathbf{C}_g \hat{f}_j \mathbf{C}_g \right]^{-1} \right]$$

and

$$\mathbb{E} \left[ \mathbf{w}_g \mathbf{D}_u \mathbf{w}_g \right] = \sum_{m=1}^{M} \xi_m^2 \sum_{n=1}^{N} \varphi_{m,n}^2 \mathbb{E} \left[ \sum_{j \in R_g} \mathbf{C}_g \hat{f}_j \mathbf{C}_g \right]^{-1} \right].$$

Combining all results completes the proof.

**APPENDIX C**

**PROOF OF THEOREM 3**

By substituting the P-MMSE vector of UAVs (12) into (13), the received signal can be rewritten as

$$\xi \varphi \mathbf{w}_g^H \sum_{i \in S_u} q_i^a \hat{g}_i^H \mathbf{D}_u \hat{g}_i + \mathbf{Z}_{S_u} + \sigma_d^2 \mathbf{I}_{NL} \right) \right]^{-1} \xi \varphi \mathbf{D}_u \mathbf{w}_g^H \right.$$

$$\sum_{i \in S_u} q_i^a \xi \varphi \mathbf{D}_u \hat{g}_i \left( \sum_{r=1}^{U} \mathbf{g}_r \mathbf{s}_r + \sum_{g=1}^{G} \mathbf{f}_g \mathbf{x}_g + \mathbf{n}_g \right) \right.$$}

$$= \sum_{i \in S_u} q_i^a \xi \varphi \mathbf{D}_u \hat{g}_i \left( \sum_{r=1}^{U} \mathbf{g}_r \mathbf{s}_r + \sum_{g=1}^{G} \mathbf{f}_g \mathbf{x}_g + \mathbf{n}_g \right) \right.$$

The instantaneous effective SINR of UAVs can be given by (C2).

$$\text{SINR}_{\text{UAV},u}^{\text{ul-MMSE}} = \sum_{i \in S_u} q_i^a \xi \varphi \mathbf{D}_u \hat{g}_i \left( \sum_{r=1}^{U} \mathbf{g}_r \mathbf{s}_r + \sum_{g=1}^{G} \mathbf{f}_g \mathbf{x}_g + \mathbf{n}_g \right) \right.$$

where

$$\xi \varphi \mathbf{D}_u \hat{g}_i \left( \sum_{r=1}^{U} \mathbf{g}_r \mathbf{s}_r + \sum_{g=1}^{G} \mathbf{f}_g \mathbf{x}_g + \mathbf{n}_g \right) \right.$$

Combining all results completes the proof.

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