Massive-MIMO Based Statistical QoS Provisioning for mURLLC Over 6G UAV Mobile Wireless Networks

Xi Zhang[†], Qixuan Zhu[†], and H. Vincent Poor[‡]

[†]Networking and Information Systems Laboratory

Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843, USA

[‡]Department of Electrical and Computer Engineering, Princeton University, Princeton, NJ 08544, USA
E-mail: {xizhang@ece.tamu.edu, qixuan@tamu.edu, poor@princeton.edu}

Abstract—The sixth generation (6G) wireless networks are required to provide the massive ultra-reliable low-latency communication (mURLLC) services for massive subscribers, and thus, need to be supported by new techniques. Since the massive multiple-input multiple-output (massive MIMO) technique with massive antennas is able to substantially improve the channel performance, it has been widely applied to achieve the goal of mURLLC networks. Moreover, based on the inherent advantages of high mobility and dynamically deployment, the emerging unmanned aerial vehicle (UAV) technique has also been considered as one of the promising candidate techniques in the 6G wireless networks. However, how to integrate the massive MIMO and UAV techniques has never been thoroughly studied. In this paper, we first establish the massive MIMO channel model between a set of UAVs and a ground station, equipped with uniform rectangular antenna array. Then, we derive the expression of channel capacity for this channel model, which is a function of the distance between each UAV and each antenna. To support the mURLLC traffics in the 6G wireless networks, we employ the effective capacity theory to measure the maximum packet arrival rate, and we also derive the upper-bound on the effective capacity, which is a function of our obtained channel capacity. Finally, we validate and evaluate our derived results of the UAV communication with massive MIMO channel over 6G wireless networks through numerical analyses.

Index Terms—The sixth generation (6G) wireless communication, unmanned aerial vehicles (UAV), uniform rectangular array (URA), massive multiple-input multiple-input (MIMO), effective capacity, statistical QoS provisioning, mURLLC.

I. Introduction

HILE the fifth generation (5G) mobile wireless network has been widely deployed, the number of mobile users and their services requirements are expected to increase exponentially. As the wireless network research has been

This work of Xi Zhang and Qixuan Zhu was supported in part by the U.S. National Science Foundation under Grants CCF-2142890, CCF-2008975, ECCS-1408601, and CNS-1205726, and the U.S. Air Force under Grant FA9453-15-C-0423. This work of H. Vincent Poor was supported in part by the U.S. National Science Foundation under Grants CCF-0939370 and CCF-1908308.

shifted toward the next sixth generation (6G) wireless communication networks, one of the key communication scenarios is the massive ultra-reliable and low-latency communication (mURLLC), where a large number of mobile users need to be served under the requirement of end-to-end transmission delay being less than 1 ms, and the packet loss probability being within 10^{-5} to 10^{-7} [1–3]. The massive multiple-input multiple-output (massive MIMO) technique [4] has attracted a lot of research attentions and has been considered as one of the promising candidate techniques to support the mURLLC wireless networks, because it is able to significantly improve wireless channel quality-of-service (QoS) performances in terms of reliability, spectral efficiency, and energy efficiency [5].

Another 6G candidate technique, called unmanned aerial vehicle (UAV), has also been proposed to potentially support the mURLLC wireless networks by significantly expanding the signal's line-of-sight (LOS) propagation area due to its flexibility to improve the wireless connection's coverage [6]. Leveraging the flexible mobility of UAV, a cooperative UAV swarm can be viewed as a dynamic antenna array to maximize the wireless channel capacity through optimizing the position of each UAV. Unlike the fixed and size limited antenna array, the UAV swarm can achieve large apertures and are not bounded to any geometry [7]. Therefore, integrating the UAV with massive MIMO techniques maximizes the channel capacity with the cost of moving the UAV from their initial positions [7].

Some works have studied the massive MIMO UAV communications in various scenarios of 6G networks. The work of [8] optimized the three-dimensional (3D) deployment by using decentralized control strategy to maximize the channel capacity of the MIMO wireless channel, where each UAV applies its local information to solve a sub-problem. The authors of [9] optimized the UAV's placement, quantization noise variance, and power control to maximize the minimum transmission rate of the massive MIMO UAV communications between UAV and ground user equipments. The authors of [4]

studied the capacity performance and polarization mismatch loss in a 3D polarization model for massive MIMO channel, deriving the closed-form expression for the lower-bound on the ergodic rate and the optimal antenna spacing which maximizes the ergodic rate. The UAV swarm position optimization scheme is proposed in [7] to attain the maximum MIMO capacity. The authors of in [7] also minimized the travel distances of UAVs while guaranteeing the channel capacity.

However, how to efficiently integrate the UAV technique with the massive MIMO communication scheme to support the mURLLC services to satisfy the low-latency transmission requirement still remains a challenging open problem. To overcome this difficulty, in this paper we apply the statistical delaybounded QoS theory, which characterizes the delay violation probability in a time-varying wireless channel, to support the low latency transmission in mURLLC over 6G wireless networks. We first establish the massive MIMO channel model for the wireless communication between a ground station (GS) and a UAV swarm, where the GS is equipped with uniform rectangular antenna array and each UAV is equipped with single antenna. We then derive the expression of the channel capacity for the UAV swarm to GS communication. The derived channel capacity is a function of the distance between each UAV to each antenna, showing that the channel capacity depends on the position of each UAV. Finally, we employ the effective capacity in statistical delay-bounded QoS theory, which measures the maximum packet arrival rate under a given exponential decaying rate of the delay violation probability, and we also calculate the upper-bound on the effective capacity using the derived channel capacity.

The rest of this paper is organized as follows. Section II establishes the massive MIMO wireless channel model from multiple UAVs to the GS equipped with uniform rectangular array. Section III derives the expression of the instantaneous channel capacity for our developed UAV-BS massive MIMO communications. Section IV derives the UAV's effective capacity and its upper-bound for supporting the statistical delay-bounded QoS guarantee. Section V validates and evaluates our derived results of UAV-BS massive MIMO communications. This paper concludes with Section VI.

II. THE SYSTEM MODELS

As shown in Fig. 1, we consider a cellular network with a fixed GS and K moving UAVs, communicating using the massive MIMO technique. The GS is equipped with the uniform rectangular array (URA) with total number of $L=L_xL_y$ antennas, and each UAV is equipped with single antenna. The distance between two antennas of the URA in both x-axis and y-axis directions is denoted by δ . Let $l \in \{1,2,\ldots,L\}$ be the index of antennas in the URA, where $l=(q-1)L_x+p$, $p \in \{1,2,\ldots,L_x\}$, and $q \in \{1,2,\ldots,L_y\}$. Assume that the first antenna of the URA is in the origin of the coordinate system. Denote by ϕ_k the *elevation angle* between the line from the kth UAV to the first antenna and the x-y plane. The

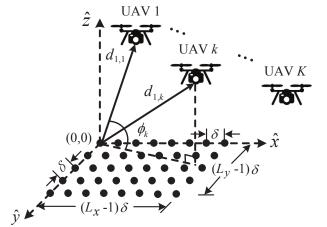


Fig. 1. The UAV's massive MIMO communications to a uniform rectangular array (URA) based ground station (GS), where \hat{x} , \hat{y} , and \hat{z} are the directions of the x-axis, y-axis, and z-axis, respectively.

distance, denoted by $d_{l,k}$, between the lth antenna and the kth UAV is given by:

$$d_{l,k} = \sqrt{(d_{1,k}\sin\phi_k)^2 + (d_{1,k}\cos\phi_k \pm \Delta_l)^2}$$
 (1)

where the sign of " \pm " using "+" if $d_{l,k} > d_{1,k}$, while using "-" if $d_{l,k} < d_{1,k}$, and Δ_l is the distance between the first and the lth antenna, which is given by:

$$\Delta_l = \sqrt{(q-1)^2 \delta^2 + (p-1)^2 \delta^2}.$$
 (2)

The channel gain, denoted by $g_{l,k}$, between the kth UAV and the lth antenna in the URA is given by [10]

$$g_{l,k} = \sqrt{\beta_k} h_{l,k} e^{-i\frac{2\pi}{\lambda} d_{l,k}} \tag{3}$$

where $\beta_k = [\lambda/(4\pi d_{l,k})]^2 \approx [\lambda/(4\pi d_{1,k})]^2$ is the large-scale fading coefficient, $h_{l,k}$ represents the effect of small-scale fading, and λ is the wavelength. Let $\mathbf{G} = [g_{l,k}] \in \mathbb{C}^{L \times K}$ be the matrix comprising the channel gains between all antennas and all UAVs. Let $\tau_{\mathrm{ul,p}}$ be the number of samples for the uplink pilot signal. Let Φ be the $\tau_{\mathrm{ul,p}} \times K$ orthogonal pilot matrix satisfying $\Phi^H \Phi = \mathbf{I}_K$, where \mathbf{I}_K is the $K \times K$ identity matrix and $(\cdot)^H$ is the Hermitian transpose. In the training phase, K UAVs are assigned K orthogonal pilot sequences and the pilot sequences are known by both UAVs and GS. Let $\mathbf{X}_p = \sqrt{\tau_{\mathrm{ul,p}}} \Phi^H$ be the pilot signal sending from UAVs to GS. The received pilot signal, denoted by \mathbf{Y}_p , at the GS is given by:

$$\mathbf{Y}_{p} = \sqrt{\tau_{\text{ul,p}}} \mathbf{G} \mathbf{X}_{p} + \mathbf{W}_{p} = \sqrt{\tau_{\text{ul,p}} \rho_{\text{ul}}} \mathbf{G} \mathbf{\Phi}^{H} + \mathbf{W}_{p}$$
 (4)

where ρ_{ul} is the transmit power over uplink and $\mathbf{W}_p \in \mathbb{R}^{L \times \tau_{ul,p}}$ is the noise matrix. According to the de-spreading of the received pilot signal scheme in [10, Section 3.1.2], the BS performs a de-spreading operation by correlating its received signals with the pilot signal. The received signal, denoted by $\overline{\mathbf{Y}}_p$, after the de-spreading operation is given by

$$\overline{\mathbf{Y}}_{p} = \mathbf{Y}_{p} \mathbf{\Phi} = \sqrt{\tau_{ul,p} \rho_{ul}} \mathbf{G} + \mathbf{W}_{p} \mathbf{\Phi}$$
 (5)

where each element of $\mathbf{W}_p \mathbf{\Phi}$ follows Gaussian distribution $\mathcal{N}(0,1)$. Using the minimum mean-square error (MMSE) estimation, the mean-square of the channel estimate, denoted by $\mathbf{\gamma} \triangleq [\gamma_1, \gamma_2, \cdots, \gamma_K]^\mathsf{T}$, is given by [10, Eq. (3.8)]:

$$\gamma_k \triangleq \mathbb{E}\left[\left|\widehat{g}_{l,k}\right|^2\right] = \frac{\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_k^2}{1 + \tau_{\text{ul,p}}\rho_{\text{ul}}\beta_k} \tag{6}$$

where $\widehat{g}_{l,k}$ is the estimated channel gain between the kth UAV and the lth antenna in the URA. Let $\mathbf{q} = [q_1, q_2, \dots, q_K]^\intercal$ be the column vector, representing the transmitted signal of all UAVs. Each element of \mathbf{q} follows Gaussian distribution $\mathcal{N}(0,1)$, and \mathbf{q} satisfies $\mathbb{E}\left[\mathbf{q}\mathbf{q}^H\right] = \mathbf{I}_k$. The kth UAV transmits a weighted symbol, denoted by x_k , as follows:

$$x_k = \sqrt{\eta_k} q_k \tag{7}$$

where $\eta_k \in [0, 1]$ is the power control coefficient for the kth UAV. The received signal, denoted by y_l , by the lth antenna of URA is

$$y_l = \sqrt{\rho_{\text{ul}}} \sum_{k=1}^K g_{l,k} x_k + w_l \tag{8}$$

where w_l is the receiver noise, following Gaussian distribution $\mathcal{N}(0,1)$. Thus, the $L \times 1$ received signal by URA is

$$\mathbf{y} = \sqrt{\rho_{\text{ul}}} \mathbf{G} \mathbf{\Omega}_{\boldsymbol{\eta}}^{\frac{1}{2}} \mathbf{q} + \mathbf{w} \tag{9}$$

where $\eta = [\eta_1, \eta_2, \cdots, \eta_K]^{\mathsf{T}}$, $\mathbf{w} = [w_1, w_2, \cdots, w_L]^{\mathsf{T}}$, $\Omega_{\boldsymbol{\eta}}$ is the diagonal matrix with elements of $\boldsymbol{\eta}$ on its diagonal, and $\Omega^{\frac{1}{2}}$ is the matrix Ω taking square root of each element. Denote by $\widetilde{\mathbf{G}}$ the matrix of channel estimation errors, and thus, we have $\mathbf{G} = \widehat{\mathbf{G}} - \widetilde{\mathbf{G}}$. Eq. (9) can be further written as

$$\mathbf{y} = \sqrt{\rho_{\text{ul}}} \widehat{\mathbf{G}} \mathbf{\Omega}_{\boldsymbol{\eta}}^{\frac{1}{2}} \mathbf{q} + \mathbf{w} - \sqrt{\rho_{\text{ul}}} \widetilde{\mathbf{G}} \mathbf{\Omega}_{\boldsymbol{\eta}}^{\frac{1}{2}} \mathbf{q}$$
 (10)

Using the maximum-ratio combining (MRC) decoder, where the linear decoding matrix is $\mathbf{A} = \widehat{\mathbf{G}}$, the output of the decoding processing, denoted by $\mathbf{r} \in \mathbb{R}^{K \times 1}$, is given by

$$\mathbf{r} = \mathbf{A}^H \mathbf{y} = \widehat{\mathbf{G}}^H \mathbf{y} \tag{11}$$

Define $\hat{\mathbf{g}}_k$ as the kth column of $\hat{\mathbf{G}}$. Since $\hat{\mathbf{g}}_k = [\hat{g}_k^1, \hat{g}_k^2, \cdots, \hat{g}_k^L]^\mathsf{T}$, the kth element of \mathbf{r} is given by:

$$r_k = \widehat{\mathbf{g}}_k^H \mathbf{y} = \sqrt{\rho_{\text{ul}} \eta_k} \widehat{\mathbf{g}}_k^H \widehat{\mathbf{g}}_k q_k + n_k \tag{12}$$

where n_k is the effective additive noise given by

$$n_{k} = \sum_{j=1, j \neq k}^{K} \sqrt{\rho_{\text{ul}} \eta_{j}} \widehat{\mathbf{g}}_{k}^{H} \widehat{\mathbf{g}}_{j} q_{j} + \widehat{\mathbf{g}}_{k}^{H} \mathbf{w} - \sum_{j=1}^{K} \sqrt{\rho_{\text{ul}} \eta_{j}} \widehat{\mathbf{g}}_{k}^{H} \widetilde{\mathbf{g}}_{j} q_{j}$$

$$(13)$$

III. INSTANTANEOUS ERGODIC RATE FOR MASSIVE MIMO COMMUNICATIONS

Let $d_k \triangleq [d_{l,k}] \in \mathbb{R}^{L \times 1}$ be the distance vector between the kth UAV and the lth antenna. Since $g_{l,k}$ is a function of $d_{l,k}$, the ergodic rate, namely channel capacity, is a function of the distance vector d_k . Define $P(d_k) \triangleq \left(\widehat{\mathbf{g}}_k^H \mathbf{g}_k\right)^2$. Using [10], the

instantaneous ergodic rate obtained from the kth UAV, denoted by $C_k(\mathbf{d}_k)$, is given by:

$$C_{k}(\boldsymbol{d}_{k}) = \log_{2}\left(1 + \frac{\rho_{\text{ul}}\eta_{k}\left(\widehat{\mathbf{g}}_{k}^{H}\widehat{\mathbf{g}}_{k}\right)^{2}}{\operatorname{Var}\left[n_{k}\right]}\right) = \log_{2}\left(1 + \frac{\rho_{\text{ul}}\eta_{k}P(\boldsymbol{d}_{k})}{\operatorname{Var}\left[n_{k}\right]}\right)$$
(14)

where $Var[\cdot]$ is the variance of a random variable. As all three terms in Eq. (13) are mutually uncorrelated [10, Section 2.3.4], we further derive $Var[n_k]$ in Eq. (14) as

$$\operatorname{Var}[n_{k}] = \operatorname{Var}\left[\sum_{j=1, j \neq k}^{K} \sqrt{\rho_{\text{ul}} \eta_{j}} \widehat{\mathbf{g}}_{k}^{H} \widehat{\mathbf{g}}_{j} q_{j}\right] + \operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H} \mathbf{w}\right]$$

$$+ \operatorname{Var}\left[\sum_{j=1}^{K} \sqrt{\rho_{\text{ul}} \eta_{j}} \widehat{\mathbf{g}}_{k}^{H} \widetilde{\mathbf{g}}_{j} q_{j}\right]$$

$$= \rho_{\text{ul}} \sum_{j=1, j \neq k}^{K} \eta_{j} \gamma_{j} \operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H} \widehat{\mathbf{g}}_{j}\right] + \operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H} \mathbf{w}\right]$$

$$+ \rho_{\text{ul}} \sum_{j=1}^{K} \eta_{j} \operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H} \widetilde{\mathbf{g}}_{j}\right] \qquad (15)$$

Since $\operatorname{Var}\left[\sum_{i}X_{i}\right] = \sum_{i}\operatorname{Var}\left[X_{i}\right]$ if $X_{i}, \forall i$, are mutually uncorrelated, and $\operatorname{Var}\left[XY\right] = \mathbb{E}\left[X^{2}\right]\mathbb{E}\left[Y^{2}\right] - \left(\mathbb{E}\left[X\right]\right)^{2}\left(\mathbb{E}\left[Y\right]\right)^{2}$ if X and Y are two independent random variables, where $\mathbb{E}[\cdot]$ is the expectation, we can further derive $\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\widehat{\mathbf{g}}_{j}\right]$, $\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\mathbf{w}\right]$, and $\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\widetilde{\mathbf{g}}_{j}\right]$, respectively, as follows:

$$\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\widehat{\mathbf{g}}_{j}\right] = \sum_{l=1}^{L} \left(\mathbb{E}\left[\widehat{g}_{l,k}^{2}\right] \mathbb{E}\left[\widehat{g}_{l,j}^{2}\right] - \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[\widehat{g}_{l,j}\right]\right)^{2} \right)$$

$$= L\gamma_{k}\gamma_{j} - \sum_{l=1}^{L} \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[\widehat{g}_{l,j}\right]\right)^{2}$$

$$(16)$$

and

$$\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\mathbf{w}\right] = \sum_{l=1}^{L} \left(\mathbb{E}\left[\widehat{g}_{l,k}^{2}\right] \mathbb{E}\left[w_{l}^{2}\right] - \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[w_{l}\right]\right)^{2}\right)$$

$$= \sum_{l=1}^{L} \mathbb{E}\left[\left(\widehat{g}_{l,k}\right)^{2}\right] = \mathbb{E}\left[\|\widehat{\mathbf{g}}_{k}\|^{2}\right] = L\gamma_{k}$$
(17)

where $\|\cdot\|$ is the ℓ_2 norm, and

$$\operatorname{Var}\left[\widehat{\mathbf{g}}_{k}^{H}\widetilde{\mathbf{g}}_{j}\right] = \sum_{l=1}^{L} \left(\mathbb{E}\left[\widehat{g}_{l,k}^{2}\right] \mathbb{E}\left[\widetilde{g}_{l,j}^{2}\right] - \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[\widetilde{g}_{l,j}\right]\right)^{2}\right)$$

$$\stackrel{\text{(a)}}{=} \sum_{l=1}^{L} \left(\gamma_{k}(\beta_{j} - \gamma_{j}) - \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[\widetilde{g}_{l,j}\right]\right)^{2}\right)$$

$$= L\gamma_{k}(\beta_{j} - \gamma_{j}) - \sum_{l=1}^{L} \left(\mathbb{E}\left[\widehat{g}_{l,k}\right]\right)^{2} \left(\mathbb{E}\left[\widetilde{g}_{l,j}\right]\right)^{2}$$

$$(18)$$

where (a) is due to [10, Eq. (3.10)]. Throughout this paper, the expectation for $g_{l,k}$, $\tilde{g}_{l,k}$, or $\tilde{g}_{l,k}$ is taken with respect to

the random variable $h_{l,k}$ since they are functions of $h_{l,k}$. We can also derive $\mathbb{E}\left[\widehat{g}_{l,k}\right]$ and $\mathbb{E}\left[\widetilde{g}_{l,j}\right]$, respectively, as follows:

$$\mathbb{E}\left[\widehat{g}_{l,k}\right] \stackrel{\text{(b)}}{=} \mathbb{E}\left[\frac{\sqrt{\tau_{\text{ul,p}}\rho_{\text{ul}}}\beta_{k}}{1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}\left[\overline{\mathbf{Y}}_{p}\right]_{l,k}\right] \stackrel{\text{(c)}}{=} \mathbb{E}\left[\frac{\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}{1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}g_{l,k}\right] \\
= \frac{\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}^{\frac{3}{2}}}{1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}e^{-i\frac{2\pi}{\lambda}d_{l,k}}\mathbb{E}\left[h_{l,k}\right] \tag{19}$$

where (b) is due to [10, Eq. (3.7)] and (c) holds due to Eq. (5), and

$$\mathbb{E}\left[\widetilde{g}_{l,j}\right] = \mathbb{E}\left[\widehat{g}_{l,j} - g_{l,j}\right] = -\mathbb{E}\left[\frac{g_{l,j}}{1 + \tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{j}}\right]$$

$$= -\frac{\beta_{j}^{\frac{1}{2}}e^{-i\frac{2\pi}{\lambda}d_{l,j}}}{1 + \tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{j}}\mathbb{E}[h_{l,k}]. \tag{20}$$

Defining $\mathbb{E}[h_{l,k}] = \overline{h}$ and plugging Eqs. (16)-(20) into Eq. (15), we have

$$\operatorname{Var}[n_{k}] = L\gamma_{k} \left[\rho_{\mathrm{ul}} \sum_{j=1, j \neq k}^{K} \eta_{j} \gamma_{j}^{2} + \rho_{\mathrm{ul}} \sum_{j=1}^{K} \eta_{j} (\beta_{j} - \gamma_{j}) + 1 \right] \\
- \rho_{\mathrm{ul}} \sum_{j=1, j \neq k}^{K} \eta_{j} \gamma_{j} \left[\sum_{l=1}^{L} \left(\mathbb{E} \left[\widehat{g}_{l,k} \right] \right)^{2} \left(\mathbb{E} \left[\widehat{g}_{l,j} \right] \right)^{2} \right] \\
- \rho_{\mathrm{ul}} \sum_{j=1}^{K} \eta_{j} \left[\sum_{l=1}^{L} \left(\mathbb{E} \left[\widehat{g}_{l,k} \right] \right)^{2} \left(\mathbb{E} \left[\widetilde{g}_{l,j} \right] \right)^{2} \right] \\
= L\gamma_{k} M_{1} + \frac{L\gamma_{k} \rho_{\mathrm{ul}} \eta_{k} \beta_{k}}{1 + \tau_{\mathrm{ul},p} \rho_{\mathrm{ul}} \beta_{k}} \\
- \left(\tau_{\mathrm{ul},p}^{2} \rho_{\mathrm{ul}}^{2} M_{2} + M_{3} \right) c_{1}(\beta_{k}) - c_{2}(\beta_{k}) \tag{21}$$

where M_1 , M_2 , and M_3 only depend on the distance $d_{l,j}$ of other UAVs (i.e., the *j*th UAV, $\forall j \neq k$), which are defined as:

$$M_{1} \triangleq \rho_{\text{ul}} \sum_{j=1, j \neq k}^{K} \eta_{j} \gamma_{j}^{2} + \rho_{\text{ul}} \sum_{j=1, j \neq k}^{K} \eta_{j} (\beta_{j} - \gamma_{j}) + 1$$

$$M_{2} \triangleq \sum_{j=1, j \neq k}^{K} \eta_{j} \gamma_{j} \frac{\beta_{j}^{3} e^{-i\frac{4\pi}{\lambda} d_{l,j}}}{(1 + \tau_{\text{ul},p} \rho_{\text{ul}} \beta_{j})^{2}}$$

$$M_{3} \triangleq \sum_{j=1, j \neq k}^{K} \eta_{j} \frac{\beta_{j} e^{-i\frac{4\pi}{\lambda} d_{l,j}}}{(1 + \tau_{\text{ul},p} \rho_{\text{ul}} \beta_{j})^{2}}$$
(22)

and $c_1(\beta_k)$ and $c_2(\beta_k)$ are functions of β_k , which are given by:

$$c_{1}(\beta_{k}) = \frac{L\tau_{\text{ul,p}}^{2}\rho_{\text{ul}}^{3}\beta_{k}^{3}\overline{h}^{4}e^{-i\frac{4\pi}{\lambda}d_{l,k}}}{(1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{2}}$$

$$c_{2}(\beta_{k}) = \frac{L\tau_{\text{ul,p}}^{2}\rho_{\text{ul}}^{3}\beta_{k}^{4}\overline{h}^{4}\eta_{k}e^{-i\frac{8\pi}{\lambda}d_{l,k}}}{(1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{4}}$$
(23)

Using [10, Eq. (3.7)] again, we derive $P(\mathbf{d}_k) = (\widehat{\mathbf{g}}_k^H \widehat{\mathbf{g}}_k)^2$ in Eq. (14) as follows:

$$(\widehat{\mathbf{g}}_{k}^{H}\widehat{\mathbf{g}}_{k})^{2} = \left(\sum_{l=1}^{L} \widehat{g}_{l,k}\widehat{g}_{l,k}\right)^{2} = \left(\sum_{l=1}^{L} \left(\frac{\sqrt{\tau_{\text{ul,p}}\rho_{\text{ul}}}\beta_{k}}{1 + \tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}} \left[\overline{\mathbf{Y}}_{p}\right]_{l,k}\right)^{2}\right)^{2}$$

$$\approx \frac{L^{2}(\tau_{\text{ul,p}}\rho_{\text{ul}})^{2}\beta_{k}^{4}}{(1 + \tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{4}} \left[(\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{2}h_{l,k}^{4}e^{-i\frac{8\pi}{\lambda}d_{1,k}} + \overline{w}_{1,k}^{4}\right]$$

$$+ 6\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}h_{l,k}^{2}e^{-i\frac{4\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}^{2}$$

$$+ 4(\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{\frac{3}{2}}h_{l,k}^{3}e^{-i\frac{6\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}$$

$$+ 4\sqrt{\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}h_{l,k}e^{-i\frac{2\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}^{3}$$

$$(24)$$

where $\overline{w}_{1,k}$ is the entry in the *l*th row and *k*th column of the matrix $\overline{\mathbf{W}}_p = \mathbf{W}_p \mathbf{\Phi}$. Thus, the closed-form expression of channel capacity $C_k(\mathbf{d}_k)$ can be obtained by plugging Eq. (24) and Eq. (21) into Eq. (14).

IV. EFFECTIVE CAPACITY FOR STATISTICAL DELAY-BOUNDED QOS PROVISIONING UNDER MASSIVE MIMO COMMUNICATIONS

To achieve the low latency transmission in the mURLLC mobile wireless networks, we use the statistical delay-bounded QoS provisioning theory [11–15] to characterize the delay violation probability in a time-varying wireless channel. We use an important performance *effective capacity* in statistical delay-bounded QoS provisioning theory to measure the maximum packets arrival rate under the QoS exponent θ , where θ is the exponential decaying rate of the packet delay violation probability. A smaller value of θ implies that the mURLLC wireless channel can only provide a looser latency guarantee, while a larger value of θ means that a more stringent latency requirement can be supported. Denote by $EC_k(\theta, d_k)$ the effective capacity of this massive-MIMO comprised of L antennas and the kth UAVs. Thus, we obtain the effective capacity $EC_k(\theta, d_k)$ as follows:

$$EC_{k}(\theta, \boldsymbol{d}_{k}) = -\frac{1}{\theta} \log \left(\mathbb{E} \left[e^{-\theta C_{k}(\boldsymbol{d}_{k})} \right] \right)$$

$$= -\frac{1}{\theta} \log \left(\mathbb{E} \left[\left(1 + \frac{\rho_{\text{ul}} \eta_{k} P(\boldsymbol{d}_{k})}{\text{Var} \left[n_{k} \right]} \right)^{\alpha} \right] \right)$$

$$\stackrel{\text{(d)}}{\leq} -\frac{\alpha}{\theta} \log \left(1 + \frac{\rho_{\text{ul}} \eta_{k} \mathbb{E} \left[P(\boldsymbol{d}_{k}) \right]}{\text{Var} \left[n_{k} \right]} \right)$$
(25)

where $\alpha \triangleq -\theta/\log 2$ and (d) is due to Jensen's inequality where $\mathbb{E}[f(x)] \geq f(\mathbb{E}[x])$ for a convex function f(x). Assuming that $h_{l,k}$ follows Nakagami-m distribution with mean of \overline{h} , the probability density function (pdf) of $h_{l,k}$, denoted by $f_{h_{l,k}}(h)$, is given by:

$$f_{h_{l,k}}(h) = \frac{h^{m-1}}{\Gamma(m)} \left(\frac{m}{\overline{h}}\right)^m \exp\left(-\frac{m}{\overline{h}}h\right)$$
 (26)

where m is the fading parameter of Nakagami-m distribution, \overline{h} is the average of $h_{l,k}, \forall k, \Gamma(\cdot)$ is the Gamma function. Using the pdf of $h_{l,k}$, we can derive $\mathbb{E}\left[h_{l,k}^2\right] = \overline{h}^2$, $\mathbb{E}\left[h_{l,k}^3\right] = \overline{h}^3$,

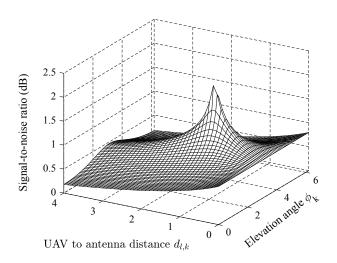


Fig. 2. The signal-to-noise ratio $(\widehat{\mathbf{g}}_k^H \widehat{\mathbf{g}}_k)^2/\mathrm{Var}[n_k^2]$ with respect to elevation angle ϕ_k and UAV to antenna distance $d_{l,k}$ given all other UAVs' positions.

 $\mathbb{E}\left[h_{l,k}^4\right] = \overline{h}^4$. Thus, the closed-form expression of $\mathbb{E}\left[P(d_k)\right]$ can be given by

$$\mathbb{E}\left[P(\mathbf{d}_{k})\right] = \mathbb{E}\left[\left(\widehat{\mathbf{g}}_{k}^{H}\widehat{\mathbf{g}}_{k}\right)^{2}\right] \\
= \frac{L^{2}(\tau_{\text{ul,p}}\rho_{\text{ul}})^{2}\beta_{k}^{4}}{\left(1+\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}\right)^{4}}\left[\left(\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}\right)^{2}e^{-i\frac{8\pi}{\lambda}d_{1,k}}\overline{h}^{4} + \overline{w}_{1,k}^{4}\right] \\
+ 6\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}e^{-i\frac{4\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}^{2}\overline{h}^{2} \\
+ 4(\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k})^{\frac{3}{2}}e^{-i\frac{6\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}\overline{h}^{3} \\
+ 4\sqrt{\tau_{\text{ul,p}}\rho_{\text{ul}}\beta_{k}}e^{-i\frac{2\pi}{\lambda}d_{1,k}}\overline{w}_{1,k}^{3}\overline{h}\right]. \tag{27}$$

To maximize the effective capacity $EC_k(\theta, \mathbf{d}_k)$, we can derive the optimal distance, denoted by $d_{l,k}^*$, between the lth antenna and the kth UAV as follows:

$$d_{l,k}^* = \arg\max_{d_{l,k}} \left\{ EC_k(\theta, \boldsymbol{d}_k) \right\} = \arg\max_{d_{l,k}} \left\{ \frac{\mathbb{E}\left[P(\boldsymbol{d}_k)\right]}{\operatorname{Var}\left[n_k\right]} \right\}.$$
(28)

Taking the first order derivative of $\frac{\mathbb{E}[P(d_k)]}{\operatorname{Var}[n_k]}$ with respect to $d_{l,k}$, the optimal distance $d_{l,k}^*$ is the solution of Eq. (29) given at the bottom of this page. As $d_{l,k}$ is a function of $d_{1,k}$, we can derive the optimal $d_{1,k}$, denoted by $d_{1,k}^*$, if we obtain $d_{l,k}^*$.

Plugging the optimal $d_{1,k}^*$ and $d_{l,k}^*$ into Eq. (27) and Eq. (21), repectively, and plugging the obtained results into Eq. (25), we can obtain the *upper-bound* of effective capacity $EC_k(\theta, \mathbf{d}_k)$.

V. PERFORMANCE EVALUATIONS

We plot the signal-to-noise ratio (SNR), denoted by $(\widehat{\mathbf{g}}_k^H \widehat{\mathbf{g}}_k)^2/\mathrm{Var}[n_k^2]$, under different values of elevation angle ϕ_k and UAV to antenna distance $d_{l,k}$ in Fig. 2. We set $L=100, K=10, \lambda=100\mathrm{m}, \overline{w}_{l,k} \sim \mathcal{N}(0,1), \tau_{\mathrm{ul,p}}=15, \rho_{\mathrm{ul}}=1\mathrm{W},$ and $\eta_k=0.5.$ Assume that the values of $d_{l,j}, \forall j \neq k$, for all other UAVs except k are given. We can obtain from Fig. 2 that there exists an optimal combination of distance $d_{l,k}$ and elevation angle ϕ_k that maximizes SNR if all the other UAVs' positions are known, showing the existance of the solution for Eq. (29). Thus, we can maximize the massive-MIMO's channel capacity through optimizing UAV's position.

Fig. 3 plots the channel gain $g_{l,k}$ under different values of distance from the kth UAV to the first antenna $d_{1,k}$ and different small-scale fading distributions. We can observe from Fig. 3 that, in the elevation angle ϕ_k 's range $[0,2\pi]$, we can obtain an optimal angle ϕ_k to maximize the channel gain. We can also observe that this optimal angle is independent of small-scale fading $h_{l,k}$'s distribution and the distance $d_{1,k}$.

In Fig. 4, we plot the effective capacity $EC_k(\theta, d_k)$ under different values of statistical delay-bounded QoS exponent θ , and compare it under small-scale fading power $h_{l,k}$ following Nakagami-m distribution and Gaussian distribution, respectively. We can observe from Fig. 4 that the effective capacity decreases as the QoS exponent θ increases. This is because a larger QoS exponent indicates a more stringent delay QoS requirement, and thus, the wireless system can only support a smaller value of packet arrival rate. We can also observe from Fig. 4 that for the same value of QoS exponent θ , the better channel quality can support a larger value of effective capacity.

Fig. 5 compares the actual velue of effective capacity $EC_k(\theta, \mathbf{d}_k)$ with its upper-bound under different numbers of antennas L on ground station. We set the other parameters are the same as in Fig. 2. We can observe from Fig. 5 that the effective capacity $EC_k(\theta, \mathbf{d}_k)$ increases as the number of antennas L and the fading parameter m increase. Because the larger m indicates the better channel quality. We also observe that the upper-bound is more tight when L is small.

$$4\left[\frac{\frac{\partial\beta_{k}}{\partial d_{l,k}}(1+2\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k})}{1+\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k}}\left(\sqrt{\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k}}e^{-i\frac{2\pi}{\lambda}d_{1,k}}\overline{h}+\overline{w}_{1,k}\right)+\beta_{k}\left(\frac{1}{2}\beta_{k}^{-\frac{1}{2}}\frac{\partial\beta_{k}}{\partial d_{l,k}}-i\frac{2\pi}{\lambda}\sqrt{\beta_{k}}\right)\sqrt{\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}}e^{-i\frac{2\pi}{\lambda}d_{1,k}}\overline{h}\right]\mathrm{Var}[n_{k}]$$

$$=\beta_{k}\left(\sqrt{\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k}}e^{-i\frac{2\pi}{\lambda}d_{1,k}}\overline{h}+\overline{w}_{1,k}\right)\left[LM_{1}\frac{\partial\beta_{k}}{\partial d_{l,k}}\frac{2\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k}+\tau_{\mathrm{ul,p}}^{2}\rho_{\mathrm{ul}}^{2}\beta_{k}^{2}}{(1+\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k})^{2}}+L\eta_{k}\frac{\partial\beta_{k}}{\partial d_{l,k}}\frac{\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}^{2}\beta_{k}^{2}(3+\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k})}{(1+\tau_{\mathrm{ul,p}}\rho_{\mathrm{ul}}\beta_{k})^{3}}\right]$$

$$-(\tau_{\mathrm{ul,p}}^{2}\rho_{\mathrm{ul}}^{2}M_{2}+M_{3})\frac{\partial c_{1}(\beta_{k})}{\partial d_{l,k}}-\frac{\partial c_{2}(\beta_{k})}{\partial d_{l,k}}\right] (29)$$

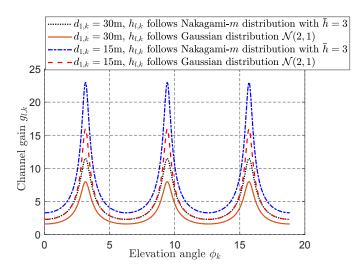


Fig. 3. Channel gain $g_{l,k}$ under different values of distance from the kth UAV to the first antenna $d_{1,k}$ and different small-scale distributions.

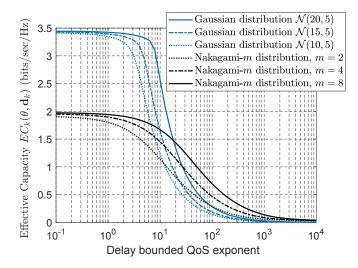


Fig. 4. Effective capacity $EC_k(\theta, \mathbf{d}_k)$ under different values of statistical QoS exponent θ .

VI. CONCLUSIONS

We have integrated the UAV systems with massive MIMO techniques to guarantee the low-latency transmission for mURLLC traffics in supporting 6G wireless networks. Since the estimated channel gain for each single channel depends on the distance between each UAV and each antenna in the ground station, we have derived the channel capacity for massive MIMO link as a function of each UVA's geometric position and the optimal UAV to antenna distance which maximizes the channel capacity. To characterize the maximum packet arrival rate for the mURLLC communication, we have also derived the upper-bound on the effective capacity.

REFERENCES

 "3GPP TSG RAN WG1 Meeting #87," Reno, Nevada, USA, 14th – 18th November 2016.

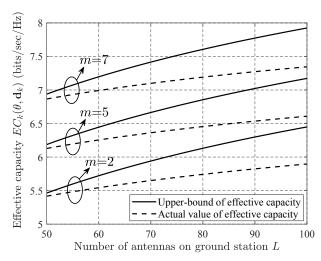


Fig. 5. Comparisons of the actual velue of effective capacity $EC_k(\theta, \boldsymbol{d}_k)$ with its upper-bound.

- [2] "Chairman's notes 3GPP: 3GPP TSG RAN WG1 Meeting 88bis," April 2017. [Online]. Available: http://www.3gpp.org/ftp/TSG_RAN/WG1_ RL1/TSGR1_88b/Report/
- [3] X. Zhang, Q. Zhu, and H. V. Poor, "Age-of-information for mURLLC over 6G multimedia wireless networks," in *Proc. 55th Annual Confer*ence on Information Sciences and Systems (CISS), 2021.
- [4] P. Chandhar, D. Danev, and E. G. Larsson, "Massive MIMO for communications with drone swarms," *IEEE Transactions on Wireless Communications*, vol. 17, no. 3, pp. 1604–1629, 2018.
- [5] X. Gao, O. Edfors, F. Rusek, and F. Tufvesson, "Massive MIMO performance evaluation based on measured propagation data," *IEEE Transactions on Wireless Communications*, vol. 14, no. 7, pp. 3899–3911, 2015.
- [6] Y. Cai, Z. Wei, R. Li, D. W. K. Ng, and J. Yuan, "Joint trajectory and resource allocation design for energy-efficient secure UAV communication systems," *IEEE Transactions on Communications*, vol. 68, no. 7, pp. 4536–4553, 2020.
- [7] S. Hanna, E. Krijestorac, and D. Cabric, "UAV swarm position optimization for high capacity MIMO backhaul," *IEEE Journal on Selected Areas in Communications*, 2021.
- [8] N. Gao, X. Li, S. Jin, and M. Matthaiou, "3-D deployment of UAV swarm for massive MIMO communications," *IEEE Journal on Selected Areas in Communications*, 2021.
- [9] Y. Huang and A. Ikhlef, "Joint design of fronthaul and access links in massive MIMO multi-UAV-enabled CRANs," *IEEE Wireless Communi*cations Letters, pp. 1–5, 2021.
- [10] T. L. Marzetta, E. G. Larsson, H. Yang, and H. Q. Ngo, Fundamentals of Massive MIMO. Cambridge University Press, 2016.
- [11] H. Su and X. Zhang, "Cross-layer based opportunistic MAC protocols for QoS provisionings over cognitive radio wireless networks," *IEEE Journal on Selected Areas in Communications*, vol. 26, no. 1, pp. 118–129, 2008.
- [12] J. Tang and X. Zhang, "Quality-of-service driven power and rate adaptation over wireless links," *IEEE Transactions on Wireless Communications*, vol. 6, no. 8, pp. 3058–3068, 2007.
- [13] H. Su and X. Zhang, "Clustering-based multichannel MAC protocols for QoS provisionings over vehicular ad hoc networks," *IEEE Transactions* on Vehicular Technology, vol. 56, no. 6, pp. 3309–3323, 2007.
- [14] J. Tang and X. Zhang, "Cross-layer resource allocation over wireless relay networks for quality of service provisioning," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 4, pp. 645–656, 2007.
- [15] X. Zhang, J. Tang, H.-H. Chen, S. Ci, and M. Guizani, "Cross-layer-based modeling for quality of service guarantees in mobile wireless networks," *IEEE Communications Magazine*, vol. 44, no. 1, pp. 100–106, 2006.