Performance of Multiuser Downlink Cell-Free Massive MIMO Systems with Hard Deadlines

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ABSTRACT Cell-free massive MIMO (mMIMO) is expected to be a novel network architecture to support massive connections, ultra-high transmission rate, and ultra-reliability low-latency transmission. Therefore, applications in ultra-reliable low-latency communications (URLLC) can be served by the cell-free mMIMO network in the future. This paper considers a multiuser downlink cell-free massive MIMO communication system and defines two events to evaluate the system’s failure in latency and reliability performance of the transmission. The first kind of event is defined as Transmission Error, where the value of the downlink rate becomes too high to be supported by the channel between the access points (APs) and user equipments (UEs), while the second event is defined as Time Overflow, where the time of packet delivery violates the hard deadline. The probabilities of these events can help evaluate the URLLC performance of the system because the probability of Transmission Error reflects the reliability of the transmission while the probability of Time Overflow reflects the latency of the transmission. We derive the expressions of the probabilities of these two events and the final probability system outage, with maximum ratio transmission (MRT) and zero-forcing (ZF) precoding, based on the properties of Gamma distribution and the approximation for non-isotropic vectors. We finally provide the numerical results by system-level simulations to show that the expressions are accurate and discuss the influence of the noise variance, the number of UEs, and the precoding scheme on the URLLC performance.

INDEX TERMS URLLC, Cell-Free Massive MIMO, Outage performance.

I. INTRODUCTION

The Massive multiple-input multiple-output (mMIMO) is regarded as an essential 5G technology [1], [2]. The cellular network infrastructure is often deployed in conventional mMIMO. In such a scenario, each base station (BS) equipped with 128 or more antennas serves a set of user equipments (UEs) [3]. The spectral efficiency is improved via spatial multiplexing, and the data rates become far higher than before. However, the inter-cell interference and weak service at the cell edge become the main challenge [4].

The cell-free massive MIMO is considered an alternative network structure where the cell boundaries are eradicated. This method deploys plenty of access points (APs) serving the UEs by coherent joint transmission. All the APs connect to a controller, also called a central processing unit (CPU), edge-cloud processor [5], or cloud radio access network (C-RAN) data center [6], via fronthaul links. In a cell-free mMIMO system, a large number of antennas are spatially distributed rather than co-located at the BS. Each UE in the system is served by all APs and therefore has uniformly good service with each other in the same time and frequency resources. Another significant advantage of the cell-free mMIMO system is that it takes the benefit of spatial multiplexing to improve SE, as [7] shows that the cell-free mMIMO can achieve remarkable improvements in the median and 95%-likely spectral efficiency (SE).

A broad interest is growing in the cell-free mMIMO topic, as the framework is considered a candidate architecture for future networks. [8] investigates conjugate beamforming and the achievable rates with conjugate beamforming and zero-forcing (ZF) precoding. CSI acquisition and data sharing among the APs are analyzed in [9], while [10] researched
the potentials of the cell-free mMIMO, which can provide a high rate, reliability, and energy efficiency with simple signal processing. Four different implementations of cell-free mMIMO, characterized by different degrees of cooperation among the APs, are studied in [11]. Moreover, [12] provides a scalable framework and algorithm for the cell-free mMIMO system. [13] also proposes an optimization framework to improve the transmission accuracy for non-orthogonal wireless backhaul in the cell-free mMIMO with a deep neural network model. All the research improves the transmission reliability and reduces the transmission latency in the cell-free mMIMO. Hence, it enables the cell-free mMIMO better to serve ultra-reliable low-latency communications (URLLC) applications.

As the cell-free mMIMO is expected to be the key 6G technology to support massive connects, ultra-high data rate, and ultra-reliability low-latency transmission [14], [15], we notice that the research on ergodic capacity cannot accurately reflect the reliability and delay performance of the communication system. For applications in URLLC scene, a new metric to quantify the latency and reliability is needed. Inspired by [16], we define two events that will cause system outage, referring to the system’s failure in latency and reliability, respectively. The lower probabilities of these outage events refer to a better performance in the reliability and latency of the transmission for URLLC applications. Therefore, the system outage probability can be treated as a metric to evaluate the URLLC performance.

This paper considers a multiuser downlink cell-free massive MIMO communication system to derive the expressions of the probabilities of the two events above, considering the multiuser interference. The first kind of event, referred to as Transmission Error, is caused by the chosen rate getting higher than the capacity of wireless channels between the UEs and APs such that the reliability of the transmission cannot be promised. The other kind of event, referred to as Time Overflow, is caused by the violation of transmission by an expected hard deadline. We find expressions for the probabilities of transmission error, time overflow, and system outage with maximum ratio transmission (MRT) and ZF precoding. Moreover, we simulate such a system to verify our expressions by comparing them with the numerical simulations. It shows that our expressions are accurate, and the noise variance, the number of UEs, and the precoding scheme affect the probabilities to varying degrees.

The rest of the paper is organized as follows. We introduce the downlink cell-free massive MIMO system model and define the two events that will lead to the system outage in Section II. Then, we analyze the corresponding expression for the probabilities of the events in Section III. Section IV presents the numerical analysis based on simulation results. Finally, our conclusion of the paper is presented in V.

Notations: We use boldface uppercase letters \( \mathbf{A} \) to denote a matrix and \( a_i \) to denote the \( i \)-th column vector of matrix \( \mathbf{A} \). We also use boldface lowercase letters \( \mathbf{b} \) to denote a column vector, while \( b_j \) and \( \| \mathbf{b} \| \) denote the \( j \)-th element and the Euclidean norm of vector \( \mathbf{b} \), respectively. The operators \((\cdot)^{\mathbb{H}}\) and \((\cdot)^{\mathbb{T}}\) are used as the hermitian transpose and Hermitian transpose operators, respectively, while the conjugate of a complex number \( z \) is denoted by \( z^* \). We use \( \mathcal{C}\mathcal{N} (\cdot,\cdot) \) to refer to the circularly symmetric complex Gaussian distribution, while \( \Gamma (\cdot,\cdot) \) refers to Gamma distribution. The expectations and covariances are denoted by \( \mathbb{E} [\cdot] \) and \( \text{Var} [\cdot] \).

II. SYSTEM MODEL AND SYSTEM OUTAGE

A. SYSTEM SETUP

In this paper, we consider a periodic multiuser downlink cell-free massive MIMO communication system depicted in Fig. 1. There are \( L \) geographically distributed single-antenna APs and \( K \) single-antenna UEs. All APs are wired to a controller, called CPU [5], [17], in an arbitrary fashion. In addition, the channel state information (CSI) is shared among the APs for their cooperative transmission. We assume the system uses the standard time-division duplex (TDD) protocol in [18] and operates in cycles of period \( T \) over a bandwidth of \( W \) Hertz. The period can be divided into two phases: an uplink training phase of duration \( T_U \) and a downlink data phase of duration \( T_D \), which means \( T = T_U + T_D \). In addition, the system expects downlink data of fixed length, \( B \) bits, to be transmitted to each UE.

![FIGURE 1. The multiuser downlink cell-free mMIMO system.](image-url)
B. CHANNEL ESTIMATION AND RATE SELECTION

We assume that there are \( \tau_p \) mutually orthogonal \( \tau_p \)-length pilot signals assigned to UEs in the system. We use \( \mathcal{A}_i \subset \{1, 2, \cdots, K\} \) to denote the subset of UEs assigned to pilot \( t \). Therefore, the received signal \( y_{tl} \) after correlating at AP \( l \) is

\[
y_{tl} = \sum_{n \in \mathcal{A}_i} \sqrt{p_n} p_{nl} h_{nl} + n_{tl}
\]

where \( \tau_p \) is the processing gain, \( p_n \) refers to UE \( n \)'s transmit power, while \( n_{tl} \sim \mathcal{CN} (0, \sigma^2) \) denotes the thermal noise, and \( \sigma^2 \) refers to the noise power. So the minimum mean-squared-error (MMSE) estimate of \( h_{kl} \) for \( k \in \mathcal{A}_i \) is

\[
\hat{h}_{kl} = \sqrt{\tau_p p_n R_{kl}^\dagger} \Phi_{tl}^{-1} h_{tl}
\]

where

\[
\Phi_{tl} = \sum_{n \in \mathcal{A}_i} \tau_p p_n R_{nl} + \sigma^2
\]

is the correlation matrix of \( y_{tl} \). Therefore, the channel estimate \( \hat{h}_{kl} \) and the estimation error \( \hat{h}_{kl} = h_{kl} - \hat{h}_{kl} \) are independently distributed as \( \hat{h}_{kl} \sim \mathcal{CN} (0, \beta_{kl}) \) and \( \hat{h}_{kl} \sim \mathcal{CN} (0, \varepsilon_{kl}) \), where

\[
\beta_{kl} = \tau_p p_k \Phi_{kl}^{-1} R_{kl}^2
\]

(4a)

\[
\varepsilon_{kl} = R_{kl} - \beta_{kl}
\]

(4b)

In the paper, we assume that \( \tau_p \geq K \), so that pilot contamination can be removed. Hence, the channel estimates \( \hat{h}_{kl} \) become independent from each other. Let \( \hat{H}_k = \begin{bmatrix} \hat{h}_{k1}, \hat{h}_{k2}, \cdots, \hat{h}_{kL} \end{bmatrix}^\dagger \in \mathbb{C}^{L \times 1} \) denote the estimated channel vector for UE \( k \), while \( \hat{H} = \begin{bmatrix} \hat{h}_1, \hat{h}_2, \cdots, \hat{h}_K \end{bmatrix} \in \mathbb{C}^{L \times K} \) refers to the estimated channel matrix. Then, two conventional low complexity precoding methods are considered in this paper as

\[
\begin{cases}
  \hat{H}_k & \text{MRT} \\
  \hat{H} (\hat{H}^H \hat{H})^{-1} & \text{ZF}
\end{cases}
\]

(5)

The precoding vector \( w_k = \frac{g_k}{\|g_k\|} \), where \( g_k \) is the \( k \)-th column of matrix \( G \). Note that we use the normalized precoding vectors with both MRT and ZF precoding methods [12], which equivalently adds a constraint on the transmit power.

After channel estimation, the APs share the CSI and jointly select an appropriate downlink rate for the corresponding UE. We use \( R_k \) to refer to the rate selected by the APs for the downlink transmission to UE \( k \). Let \( T_k \) denote the time for UE \( k \) to receive the downlink signal. The APs choose the rate through transmit precoding, according to the MMSE estimation value \( \hat{h}_k \).

\[
R_k = W \log_2 \left( 1 + \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{i=1, i \neq k}^{K} \|\hat{h}_k^H w_i\|^2 + \sigma^2} \right)
\]

(6)

where \( w_k \in \mathbb{C}^{L \times 1} \) denotes the precoding vector that APs assign to UE \( k \).

Then, the received signal at \( k \)-th UE is

\[
y_k = \hat{h}_k^H \left( \sum_{i=1}^{K} w_k x_i \right) + n_k
\]

(7)

\[
y_k = \hat{h}_k^H w_k x_k + \sum_{i=1, i \neq k}^{K} \hat{h}_k^H w_i x_i + n_k
\]

where \( x_i \sim \mathcal{CN} (0, 1) \) denotes the downlink data transmitted to UE \( i \), while \( n_k \sim \mathcal{CN} (0, \sigma^2) \) refers to the noise at the \( k \)-th UE.

C. SYSTEM OUTAGE

The system outage happens when the reliability of the following downlink data transmission cannot be guaranteed as the chosen rate is too large, or when the time of the corresponding downlink data transmission goes in excess of the intended budget \( T_k \) since the chosen rate is too low. According to [16], we define the former event as transmission error (TE) and refer to the latter event as time overflow (TO).

To relate these above to the system model closely, we firstly specify these three events below:

Transmission Error (TE) [16]: When the chosen downlink rate between APs and the UE goes beyond the channel’s capacity, also called the input-output mutual information, there will be a sharp increase in the UE’s packet error probability as the UE cannot decode the downlink data correctly. The mutual information of the channel between APs and UE \( k \) is defined as in [22].

\[
C_k = W \log_2 \left( 1 + \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{i=1, i \neq k}^{K} \|\hat{h}_k^H w_i\|^2 + \sigma^2} \right)
\]

(8)

Note that the expression is raised for analysis under the infinite blocklength (IBL) assumption, while the finite blocklength (FBL) regime analysis will be deferred to future work. To describe the reliability of the whole system, we define the TE event as happening when one or more UEs fail to receive the corresponding data correctly. Therefore, we can express the probability of the TE event due to the device failure at UE \( k \) as

\[
P \left[ \text{TE}_k \right] = P \left[ R_k > C_k \right]
\]

\[
= \! P \left[ \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{i=1, i \neq k}^{K} \|\hat{h}_k^H w_i\|^2 + \sigma^2} > \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{i=1, i \neq k}^{K} \|\hat{h}_k^H w_i\|^2 + \sigma^2} \right]
\]

(9)
By deploying the quasi-static setting, the above probability can be written in terms of the relative values of the two signal-to-interference-and-noise ratio (SINR) terms in the expressions of \( R_k \) and \( C_k \). Hence, the probability of the TE event is expressed via the probability of the first kind of device failure as

\[
P[TE] = 1 - \prod_{k=1}^{K} (1 - P[TE_k])
\]  

where equation holds because of independent channel fades.

**Time Overflow (TO):** When one of the UEs is in deep fade, the chosen rate will be relatively low, leading to a long time for the UE to receive the complete downlink data. Considering that there are many standard requirements of delay duration in real-time applications, the TO event is defined to happen when one or more UEs fail to obtain the entire data before the cycle edge. Therefore, the probability of the TO event due to the device failure at UE \( k \) is

\[
P[TO_k] = P[T_k > T_D] = F_{r_k}\left( \frac{B}{T_D W} \right)
\]  

where \( r_k \) denotes the SE at UE \( k \), while \( F_{r_k}(\cdot) \) is the cumulative distribution function (CDF) of \( r_k \). So the above probability can be written in terms of the required transmission duration \( T_k \) exceeding the downlink budget \( T_D \). As the TO event refers to at least one UE’s transmission time overflowing into a subsequent cycle, the probability of the TO event can be expressed via the probability of the second kind of device failure as

\[
P[TO] = 1 - \prod_{k=1}^{K} (1 - P[TO_k])
\]  

After choosing the downlink rates \( \{R_k\} \), the CPU can judge whether the TO event will happen. All APs might not transmit any data when the TO event is detected at the CPU side.

**System Outage (SO, [16]):** When the TE event or the TO event happens, the SO event is defined to happen. So combining these two events, we can express the system outage probability as

\[
P[SO] = 1 - P\left[ \bigcap_{k=1}^{K} \left\{ \frac{B}{T_D} \leq R_k \leq C_k \right\} \right]
\]  

Let \( P\left[ \frac{B}{T_D} \leq R_k \leq C_k \right] \) refers to the probability that the two kinds of device failure will not happen at UE \( k \). Combining the equation (9) and (11), the two kinds of device failure happen independently at UE \( k \). Therefore, the probability of device failure at UE \( k \) is \( P[TE_k] + P[TO_k] \). Considering the independent channel fades, the device failure at each UE happens independently. Then, we define the final probability of device failure as

\[
P[DF_k] = 1 - P\left[ \frac{B}{T_D} \leq R_k \leq C_k \right] = P[TE_k] + P[TO_k]
\]  

Due to the independent channel fades, the device failure happens independently at each UE. Therefore, the system outage probability can be rewritten as

\[
P[SO] = 1 - \prod_{k=1}^{K} (1 - P[DF_k])
\]  

So, we only need to analyze \( P[TE] \), \( P[TO] \), and \( P[SO] \) by the analysis of the probabilities of the two kinds of device failure, \( P[TE_k] \) and \( P[TO_k] \). Moreover, the probability \( P\left[ \frac{B}{T_D} \leq R_k \leq C_k \right] \) can be expressed via \( P[TE_k] \) and \( P[TO_k] \) as

\[
P\left[ \frac{B}{T_D} \leq R_k \leq C_k \right] = 1 - P[TE_k] - P[TO_k]
\]  

### III. OUTAGE ANALYSIS

In this section, we first characterize the probability of the probabilities of the two kinds of device failure \( P[TE_k] \) and \( P[TO_k] \) with MRT and ZF precoding. Then, we present the expressions of \( P[TE] \), \( P[TO] \), and \( P[SO] \) based on the these device failure probabilities. We list some lemmas which helps to derive the expressions above all.

**Lemma 1 ([23]):** If vector \( a \in \mathbb{C}^{M \times 1} \) consists of \( M \) i.i.d. \( CN(0, \sigma^2) \) elements, then \( a^H a \sim \Gamma(M, \sigma^2) \).

**Lemma 2 ([23]):** If variable \( Z \sim \Gamma(k, \theta) \), then \( E[Z] = k \theta \), \( \text{Var}[Z] = k \theta^2 \), and \( c Z \sim \Gamma(k, c \theta) \), where \( c > 0 \).

**Lemma 3 ([24]):** If random variables \( \{Z_i\} \) are independent and satisfy \( \Gamma(k_i, \theta_i) \) respectively, the sum \( \sum_i Z_i \) will satisfy

\[
E\left[ \sum_i Z_i \right] = \sum_i k_i \theta_i
\]

\[
\text{Var}\left[ \sum_i Z_i \right] = \sum_i k_i \theta_i^2
\]  

where \( \sum_i Z_i \sim \Gamma \left( \frac{\sum_i k_i \theta_i}{\theta_i}, \frac{\sum_i k_i \theta_i^2}{\theta_i^2} \right) \).

**Lemma 4 ([24]):** We can project an \( m \)-dimensional non-isotropic channel vector \( \mathbf{g}_k \sim \Gamma(k, \theta) \) onto an \( p \)-dimensional subspace. Then, the projection power obeys \( \Gamma\left( \frac{L}{m} k, \theta \right) \), where \( p = L \) with MRT precoding and \( p = L - K + 1 \) with ZF precoding, while independent vectors will be projected onto a one-dimensional subspace.

Note that we can obtain a better approximation by Lemma 4 when the path loss from UE \( k \) to each nearby AP is similar; otherwise, the degrees of freedom are overestimated [24]. However, we can adjust the number of effective dimension of the final subspace to increase the accuracy of our approximation. Then, based on the first three lemmas, we can derive the distributions of \( \mathbf{h}_k^H \mathbf{h}_k \), \( \mathbf{h}_k^H \mathbf{h}_k \), and \( \mathbf{h}_k^H \mathbf{h}_k \) as

\[
\mathbf{h}_k^H \mathbf{h}_k \sim \Gamma(k_k, \theta_k)
\]

\[
\mathbf{h}_k^H \mathbf{h}_k \sim \Gamma(k_k, \theta_k)
\]
\[ \mathbf{h}_k^H \mathbf{h}_k \sim \Gamma(\tilde{k}_k, \tilde{\theta}_k) \]  
\[ \text{where} \]
\[ k_k = \left( \sum_{l=1}^{L} R_{kl} \right)^2, \quad \theta_k = \sum_{l=1}^{L} R_{kl}^2 \]  
\[ \tilde{k}_k = \left( \sum_{l=1}^{L} \beta_{kl} \right)^2, \quad \tilde{\theta}_k = \sum_{l=1}^{L} \beta_{kl}^2 \]  
\[ \tilde{k}_k = \left( \sum_{l=1}^{L} \varepsilon_{kl} \right)^2, \quad \tilde{\theta}_k = \sum_{l=1}^{L} \varepsilon_{kl}^2 \]

A. TRANSMISSION ERROR

First of all, we calculate the probability of the first kind of device failure \( P[TE_k] \) to prepare for the calculation of \( P[TE] \). Calculating \( P[TE_k] \) needs to divide the power terms in SINR of \( R_k \) and \( C_k \) into different independent variables to get the final expression. We will decide the detailed method according to the precoding vectors.

1) \( P[TE_k] \) with MRT precoding

Considering the MRT precoding vector, we can rewrite the expression of \( P[TE_k] \) as

\[ \mathbb{P} \left[ \left\| \mathbf{h}_k^H \mathbf{w}_k \right\|^2 > \left\| \mathbf{h}_k^H \mathbf{w}_l \right\|^2 + \sigma^2 \right] = \mathbb{P} [ XV > (Y + \sigma^2) U] \]

where

\[ X = \left\| \mathbf{h}_k^H \mathbf{w}_k \right\|^2, \quad Y = \sum_{i=1, i \neq k}^{K} \left\| \mathbf{h}_k^H \mathbf{w}_i \right\|^2, \]

\[ U = \left\| \mathbf{h}_k^H \mathbf{w}_k \right\|^2 - \sum_{i=1, i \neq k}^{K} \left\| \mathbf{h}_k^H \mathbf{w}_i \right\|^2, \quad V = \sum_{i=1, i \neq k}^{K} \left\| \mathbf{h}_k^H \mathbf{w}_i \right\|^2 \]

These four variables become almost independent as the number of transmit antennas or APs grows. Moreover, it is evident that the signal term \( X \) and the interference term \( Y \) obey Gamma distribution with MRT precoding. Then, we need to analyze the distributions of the rest two variables. As for \( U \), it refers to the sum of three terms

\[ U = \left\| \mathbf{h}_k^H \mathbf{w}_k \right\|^2 + \mathbf{w}_k^H \mathbf{h}_k \mathbf{H}_k \mathbf{w}_k + \mathbf{w}_k^H \mathbf{h}_k \mathbf{H}_k \mathbf{w}_k \]

where the first term is a random variable obeying Gamma distribution. The sum of the rest two terms is a real number as the two terms are conjugated. The sum obeys Gaussian distribution according to [25]. The value of former term is mainly decided by \( \varepsilon_{kl} \), while the value of latter terms is mainly influenced by \( \beta_{kl} \). Therefore, the approximation distribution of variable \( U \) can be seen as Gaussian distribution when \( \sigma^2 \) is low, while it can be seen as Gamma distribution when \( \sigma^2 \) is large. Although \( V \) is similarly refers to the sum of these three kinds of terms, the sum of the pairs of conjugate terms is ignorable due to the independence of \( w_k, h_k, \) and \( \tilde{h}_k \). Therefore, \( V \) can be seen as a Gamma variable.

Then, we use the probability density functions (PDFs) of \( X, Y, U, \) and \( V \) to calculate \( P[TE_k] \) as

\[ P[TE_k] = \int_{0}^{+\infty} \int_{0}^{+\infty} \int_{0}^{+\infty} f_X(x) f_Y(y) f_U(u) f_V(v) \, du \, dv \, dx \]  

Step 1: Calculate the first integration \( \int_{-\infty}^{+\infty} f_{U}(u) \, du \). The CDF of variable \( U \) mainly decides the result \( F_{U}(\frac{x \cdot v}{y + \sigma^2}) \). Since \( U = \| \mathbf{h}_k^H \mathbf{w}_k \|^2 - \| \mathbf{h}_k^H \mathbf{w}_k \|^2 \), the mean and variance of \( U \) can be expressed as \( E[U] = k_k \theta_k - \tilde{k}_k \tilde{\theta}_k \) and \( \text{Var}[U] = k_k \theta_k^2 - k_k \tilde{k}_k \tilde{\theta}_k^2 \). Therefore, we have

\[ F_{U}(\frac{x \cdot v}{y + \sigma^2}) = \left\{ 1 + \frac{1}{\sqrt{2\pi}} \sum_{j=0}^{+\infty} \frac{(-1)^j (\frac{x \cdot v}{y + \sigma^2} \mu_u)^j}{j!} \right\} \]  

where

\[ \mu_u = k_k \theta_k - \tilde{k}_k \tilde{\theta}_k = \sum_{l=1}^{L} \varepsilon_{kl} \]  

\[ \sigma_u^2 = k_k \theta_k^2 - k_k \tilde{k}_k \tilde{\theta}_k^2 = \sum_{l=1}^{L} \varepsilon_{kl} (R_{kl} + \beta_{kl}) \]

\[ k_u = \frac{k_k \theta_k - k_k \tilde{\theta}_k^2}{k_k \theta_k^2 - k_k \tilde{k}_k \tilde{\theta}_k^2} = \left( \sum_{l=1}^{L} \varepsilon_{kl} \right)^2 \]

\[ \theta_u = \frac{k_k \theta_k^2 - k_k \tilde{k}_k \tilde{\theta}_k^2}{k_k \theta_k^2 - k_k \tilde{k}_k \tilde{\theta}_k^2} = \sum_{l=1}^{L} \varepsilon_{kl} \]

In addition, by using a taylor series approximation, we can make an asymptotic expansion of the results as

\[ F_{U}(\frac{x \cdot v}{y + \sigma^2}) = \left\{ 1 + \frac{1}{\sqrt{2\pi}} \sum_{j=0}^{+\infty} \frac{(-1)^j (\frac{x \cdot v}{y + \sigma^2} \mu_u)^j}{j!} \right\} \quad \text{Gaussian} \]

Step 2: Calculate the rest three integrations

\[ \int_{0}^{+\infty} f_X(x) \int_{0}^{+\infty} f_Y(y) \int_{0}^{+\infty} f_V(v) \cdot F_{U}(\frac{x \cdot v}{y + \sigma^2}) \, dv \, dx \]

The rest integrations calculate the expectations of \( X, Y, \)
where

\[ \begin{align*}
  X &= \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2, \\
  Y &= \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 - \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2
\end{align*} \]

\[ k_v = \frac{(K - 1) \left( k_k \theta_k - \mathbf{\hat{k}}_k \right)^2}{L \left( k_k \theta_k^2 - \mathbf{\hat{k}}_k \theta_k \right)^2}, \]

\[ \theta_v = \frac{k_k \theta_k^2 - \mathbf{\hat{k}}_k \theta_k}{k_k \theta_k - \mathbf{\hat{k}}_k} \]

Finally, we can calculate \( \mathbb{P}[\text{TE}_k] \) with MRT precoding according to equation (30) on the next page for UE \( k \) (\( k = 1, \cdots, K \)) in the systems.

2) \( \mathbb{P}[\text{TE}_k] \) with ZF precoding

Due to the definition, we can ignore the interference term \( \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 \) as it is far less than other terms. Therefore, \( \mathbb{P}[\text{TE}_k] \) can be rewritten as

\[ \mathbb{P} \left[ \frac{\| \mathbf{h}_k^H \mathbf{w}_k \|^2}{\sigma^2} > \frac{\| \mathbf{h}_k^H \mathbf{w}_k \|^2}{\sigma^2} + \sigma^2 \right] \]

\[ = \mathbb{P} \left[ XY > \sigma^2 \cdot U \right] \]

where

\[ X = \| \mathbf{h}_k^H \mathbf{w}_k \|^2, \quad U = \| \mathbf{h}_k^H \mathbf{w}_k \|^2 - \| \mathbf{h}_k^H \mathbf{w}_k \|^2 \]

\[ Y = \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 \]

\[ = \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 + \sum_{i=1, i \neq k}^{K} (\mathbf{w}_i^H \mathbf{h}_k \mathbf{h}_k^H \mathbf{w}_i) \]

\[ + \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 \]

\[ \approx \sum_{i=1, i \neq k}^{K} \| \mathbf{h}_k^H \mathbf{w}_i \|^2 \]

We simplify the expression of variable \( Y \) in the equation above for further computation, as the rest two sum terms in the original expression are negligible. These three variables become almost independent as the number of transmit antennas or APs grows. It is also evident that two of these variables, \( X \) and \( Y \), obey Gamma distribution with ZF precoding.

Then, we need to analyze the distribution of \( U \). Similar to analysis with MRT precoding, the approximation distribution of variable \( U \) can be seen as Gaussian distribution when \( \sigma^2 \) is low, while it can be seen as Gamma distribution when \( \sigma^2 \) is large. Therefore, we use the PDFs of \( X, Y, \) and \( U \) to express \( \mathbb{P}[\text{TE}_k] \) as

\[ \mathbb{P}[\text{TE}_k] = \int_0^{+\infty} \int_0^{+\infty} \int_{-\infty}^{+\infty} f_X(x) f_Y(y) f_U(u) \, du \, dy \, dx \]

\[ = \int_0^{+\infty} \int_0^{+\infty} \int_{-\infty}^{+\infty} f_X(x) f_Y(y) f_U(u) \, du \, dy \, dx \]

\[ = \frac{1}{\sqrt{2\pi}} \sum_{j=0}^{\infty} (-1)^j \frac{(\frac{x}{\theta} - \mu_u)^{2j+1}}{2^{j+1}(2j+1)\sigma_u^{2j+1}} \]

\[ \sum_{j=0}^{\infty} (-1)^j \frac{(\frac{x}{\theta} - \mu_u)^{2j+1}}{2^{j+1}(2j+1)\sigma_u^{2j+1}} \]
\( P_{\text{TE}_k} = \left\{ \begin{array}{ll} \frac{1}{2} + \frac{1}{2\pi} \sum_{j=0}^{\infty} \frac{(-1)^j}{j!(2j+1)} \left[ \frac{1}{k_u+1} \right] \left[ \frac{1}{k_u+j} \right] \left[ \frac{1}{(k_u+j)\theta_u^{k_u+j}} \right] \right]^{2j+1}, & \text{Gaussian } U \\
\frac{1}{(k_u+1)} \sum_{j=0}^{\infty} \frac{(-1)^j}{j!(k_u+j)\theta_u^{k_u+j}} \right] \left[ \frac{1}{k_u+j} \right] \left[ \frac{1}{(k_u+j)\theta_u^{k_u+j}} \right] \right]^{2j+1}, & \text{Gamma } U 
\end{array} \right. \) \tag{30}

Finally, we can calculate \( P_{\text{TE}_k} \) with MRT precoding according to equation (39) on the next page for UE \( k = 1, \ldots, K \) in the systems. So the probability of transmission error \( P_{\text{TE}_k} = 1 - \prod_{k=1}^{K} (1 - P_{\text{TE}_k}) \) can be obtained with \( P_{\text{TE}_k} \) with both MRT and ZF precoding.

### B. TIME OVERFLOW

Calculating the probability of the second kind of device failure \( P_{\text{TO}_k} \) is the prerequisite for the calculation of \( P_{\text{TO}_k} \). To get the final expression, we need to divide the terms in SINR of \( R_k \) into different almost independent variables. Therefore, we rewrite the expression of \( P_{\text{TO}_k} \) as

\[ P\left[ \| h_k^H w_k \|^2 < \left( 2 \frac{B}{TDW} - 1 \right) \left( \sum_{i=1,i \neq k}^{K} \| h_i^H w_i \|^2 + \sigma^2 \right) \right] = P\left[ X < \left( 2 \frac{B}{TDW} - 1 \right) (Y + \sigma^2) \right] \tag{40} \]

where \( X \) refers to the signal term \( \| h_k^H w_k \|^2 \), while \( Y \) refers to the interference term \( \sum_{i=1,i \neq k}^{K} \| h_i^H w_i \|^2 \). Based on the PDFs of \( X \) and \( Y \), we can express \( P_{\text{TO}_k} \) as

\[ P_{\text{TO}_k} = \int_0^{+\infty} \int_0^{+\infty} \left( 2 \frac{B}{TDW} - 1 \right) (y + \sigma^2) f_X(x) f_Y(y) \, dx \, dy \tag{41} \]

#### Step 1: Calculate the first integration

\[ \int_0^{+\infty} \left( 2 \frac{B}{TDW} - 1 \right) (y + \sigma^2) f_X(x) \, dx \tag{42} \]

The result is mainly decided by variable \( X \)’s CDF. We also make an asymptotic expansion for low complexity as

\[ F_X\left[ \left( 2 \frac{B}{TDW} - 1 \right) (y + \sigma^2) \right] = \frac{1}{\Gamma(k_x)}, \]

\[ \sum_{j=0}^{\infty} (-1)^j \cdot \frac{1}{j!(k_x+j)} \left[ \frac{1}{k_x+j} \right] \left[ \frac{1}{(k_x+j)\theta_x^{k_x+j}} \right] \left[ \frac{1}{\theta_x} \right]^{k_x+j} \tag{43} \]

#### Step 2: Calculate the rest integration

\[ \int_0^{+\infty} f_Y(y) \cdot F_X\left[ \left( 2 \frac{B}{TDW} - 1 \right) (y + \sigma^2) \right] \, dy \tag{44} \]

The rest integration calculate the expectation of variable \( Y \). Therefore, by replacing the Gamma variable \( Y \) with its moment, we have

\[ \int_0^{+\infty} f_Y(y) \cdot F_X\left[ \left( 2 \frac{B}{TDW} - 1 \right) (y + \sigma^2) \right] \, dy \]

\[ = \frac{1}{\theta_x^{k_x}} \Gamma(k_x) \sum_{j=0}^{\infty} (-1)^j \cdot \frac{1}{j!(k_x+j)\theta_x^{j}} \left[ (k_x \theta_x + \sigma^2) \right]^{k_x+j} \tag{45} \]

Then we determine the parameters according to the precoding vectors.

1) \( P_{\text{TO}_k} \) with MRT precoding

When calculate \( P_{\text{TO}_k} \) with MRT precoding, we set the parameters as

\[ k_x = \hat{k}_k, \theta_x = \hat{\theta}_k \tag{46a} \]

\[ k_y = \frac{K - 1}{L} \hat{k}_k, \theta_y = \hat{\theta}_k \tag{46b} \]

2) \( P_{\text{TO}_k} \) with ZF precoding

When calculate \( P_{\text{TO}_k} \) with ZF precoding, we set the parameters as

\[ k_x = \frac{L - K + 1}{L} \hat{k}_k, \theta_x = \hat{\theta}_k \tag{47a} \]

\[ k_y = \frac{K - 1}{L} \hat{k}_k, \theta_y = \hat{\theta}_k \tag{47b} \]

Finally, we can calculate \( P_{\text{TO}_k} \) with both MRT and ZF precoding according to equation (48) on the next page for UE \( k = 1, \ldots, K \) in the systems. Note that the expressions for \( k_x \) and \( k_y \) are finally decided by the precoding methods. So the probability of time overflow \( P_{\text{TO}_k} = 1 - \prod_{k=1}^{K} (1 - P_{\text{TE}_k}) \) can be obtained with \( P_{\text{TE}_k} \). Then, we calculate the probability of system outage \( P_{\text{SO}} \) by the expression as

\[ P_{\text{SO}} = 1 - \prod_{k=1}^{K} (1 - P_{\text{TE}_k} - P_{\text{TO}_k}) \tag{49} \]

### IV. NUMERICAL RESULTS

This section verifies our expressions above via a set of Monte-Carlo simulations. We plot the probability of transmission error as a function of the noise variance value and the probability of time overflow as the deadline value. In addition, we compare the theoretical expressions given above with the result of Monte-Carlo simulations to test the accuracy of the theoretical result.

We match the simulation setup with the 3GPP Urban Microcell model in [26]. In our simulation, the UEs are
It can be seen from the two figures, compared with the simulation results, the theoretical points and plot them as the fourth line. As seen from the two figures, the noise variance in Fig. 2 and Fig. 3. Then, we calculate the theoretical values of equation (30) and (39) and plot them in the corresponding figure. We pick the closest theoretical expression of the large-scale fading coefficient is

\[
R_{kl} (\text{dB}) = -30.5 - 36.7 \log_{10} \left( \frac{d_{kl}}{1 \text{ m}} \right) + F_{kl}
\]

(50)

where \(d_{kl}\) denotes the distance between UE \(k\) and AP \(l\) and \(F_{kl}\) refers to the shadow fading which only appears when the distance is large. The rest simulation parameter values are summarized in Table 1 [11], [12].

| Parameters | Values |
|------------|--------|
| Number of single-antenna APs \(L\) | 400 |
| Carrier frequency \(f_c\) | 2 GHz |
| Number of mutually orthogonal pilot signals \(\tau_p\) | 20 |
| Transmit bandwidth \(W\) | 20 MHz |
| Noise variance at the UEs \(\sigma_0^2\) | \(-174\) dBm |
| Transmit power \(P_k\) of UE \(k\) | 100 mW |
| Height difference between an AP and a UE | 10 m |
| Angular standard deviation around the nominal angle | 15° |

Firstly, we verify that the expressions of \(P[\text{TE}_k]\) with MRT and ZF precoding in Section III are accurate. We obtain the probability of transmission error of UE 1, \(P[\text{TE}_1]\), through Monte-Carlo simulations and plot it as a function of the noise variance in Fig. 2 and Fig. 3. Then, we calculate the theoretical values of equation (30) and (39) and plot them in the corresponding figure. We pick the closest theoretical points and plot them as the fourth line. As seen from the two figures, compared with the simulation results, the theoretical values are more accurate by characterizing the distribution of variable \(U\) as Gaussian distribution when noise variance is low. However, when noise variance is large, the theoretical values are more accurate by characterizing the distribution of variable \(U\) as Gamma distribution compared with the simulation values.

Secondly, we verify that the expressions of \(P[\text{TO}_k]\) with MRT and ZF precoding in Section III are accurate whether the noise variance is large or low. We get the probability of time overflow of UE 1, \(P[\text{TO}_1]\), through Monte-Carlo simulations and plot it as a function of the hard deadline value in Fig. 4 and Fig. 5. It can be seen from the two figures, the expression of \(P[\text{TO}_k]\) in equation (45) with both MRT and ZF precoding is accurate compared with the Monte-Carlo simulation results. The figure also demonstrates that the increasing noise variance \(\sigma^2\) brings about an increase in

\[
\begin{align*}
\text{ZF} : \quad P[\text{TE}_k] & = \frac{1}{2} + \frac{1}{\sqrt{2\pi}} \sum_{j=0}^{\infty} \frac{(-1)^j}{\sigma_0^{2j+1} \Gamma(k_x)} \sum_{j=0}^{\infty} \frac{(-1)^j}{(k_x + j)^{\sigma_0^{2j+1}}} \\
& \times \frac{1}{(k_x + j)^{\sigma_0^{2j+1}}} \left[ \frac{1}{\sigma^2 L} \sum_{l=1}^{L} \beta_{kl} (\sum_{x=1}^{x} \varepsilon_{x}^{kl})^{k_x+j} \right]^{\frac{1}{2j+1}}, \quad \text{Gaussian U} \\
& \quad \text{ZF} : \quad P[\text{TO}_k] = \frac{1}{\Gamma(k_x) \theta_x^2} \sum_{j=0}^{\infty} \left( \frac{2 \mu_1}{\sigma^2} - 1 \right)^{k_x+j} j! (k_x + j) \theta_x^2 \\
& \quad \times \left[ \frac{1}{\sigma^2 L} \sum_{l=1}^{L} \beta_{kl} (\sum_{x=1}^{x} \varepsilon_{x}^{kl})^{k_x+j} \right]^{(K-1)\sum_{j=1}^{L} \beta_{kl} + \sigma^2} \\
\end{align*}
\]

(39)
$P[\text{TO}_k]$, and the growth range is larger with ZF percoding.

Then, we plot the probabilities of transmission error and time overflow for different numbers of UE and different precoding methods to compare the outage performance of the systems. As can be seen from Fig. 6 and Fig. 7, systems with ZF precoding outperform systems with MRT precoding for having lower probabilities of transmission error and time overflow. Therefore, systems with ZF precoding have better outage performance. In addition, a more significant number of UEs leads to more interference and increasing probabilities of both transmission error and time overflow. Therefore, user grouping is necessary when the number of UEs grows to decrease the interference and probability of system outage.

For applications having more considerable noise variance, the probability of transmission error is low enough to satisfy the reliability required of URLLC, whatever the precoding method, according to Fig. 6. Then, the system can have a low outage probability as the length of downlink data is small enough to have a low probability of time overflow. However, transmission error probability converges to 0.5 when the noise variance is low, which will cause the system outage probability to get high. Therefore, a multiplicative utilization factor, $0 < \rho < 1$, can be introduced before the SINR term in the expressions of the chosen rate $R_k$ to obtain a lower probability of transmission error when the noise variance decreases. So the chosen rate by the APs becomes

$$R_k = W \log_2 \left(1 + \frac{\rho \left| \mathbf{h}_k^H \mathbf{w}_k \right|^2}{\sum_{i=1, i \neq k}^K \left| \mathbf{h}_k^H \mathbf{w}_i \right|^2 + \sigma^2} \right)$$  \hspace{1cm} (51)$$

Similar ways can be found in [27], [28]. Moreover, a backoff parameter outside the log-function is proposed in [16] to circumvent this problem. Both the two parameters
help decrease the probability of transmission error as the noise variance decreases. In addition, user grouping can also be introduced to obtain a lower probability of time overflow.

V. CONCLUSION

This paper modeled a multiuser, variable-rate downlink cell-free massive MIMO communication system. We defined two events that will lead to the system outage, to describe the system’s failure in latency and reliability performance of the transmission. The first kind of event was defined as Transmission Error, caused by the value of the downlink rate getting too low to be supported by the channel between the APs and UEs. The other event was defined as Time Overflow, caused by the violation of packet delivery against the hard deadline. We offered analytical methods, which used the properties of Gamma distribution and the approximation for non-isotropic vectors to derive the expressions of the probabilities of transmission error, time overflow, and system outage with MRT and ZF precoding considering the multiuser interference. The numerical results of system-level simulations presented that the expressions are accurate. Moreover, the noise variance, the number of UEs; and the precoding scheme influence the outage performance, or the URLLC performance, to varying degrees.

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