Efficient Resource Allocation in a Rateless-Coded MU-MIMO Cognitive Radio Network With QoS Provisioning and Limited Feedback

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Abstract—**In this paper, we design an efficient resource-allocation strategy for a multiuser multiple-input–multiple-output (MU-MIMO) rateless-coded cognitive radio network (CRN) with quality-of-service (QoS) provisioning. We consider a limited feedback MU-MIMO CRN, where zero-forcing beamforming (ZFBF) is performed under imperfect channel state information (CSI) at a cognitive base station to mitigate both inter- and intranetwork interferences. To minimize the total feedback amount while satisfying the interference constraint and QoS requirements simultaneously, we propose to adaptively adjust the transmit power, select the transmission mode, and choose the feedback codebook size according to the interference constraint, CSI, and QoS requirements. The optimization problem is shown to be an integer programming problem, and we propose a heuristic algorithm that can provide an optimal solution for most practical scenarios. Results show that our resource-allocation strategy can decide the feedback amount and transmission mode adaptively based on the delay requirements.**

Index Terms—**Imperfect channel state information (CSI), limited feedback, multiuser multiple-input–multiple-output (MU-MIMO) cognitive radio network (CRN), quality-of-service (QoS) guarantee, rateless coding.**

I. Introduction

To solve the contradiction that spectrum resources are in shortage while most of them are definitely underutilized in more than 70% of the time [1], cognitive radio is proposed to improve spectral efficiency through spectrum sharing between primary and cognitive networks as long as the interference from the cognitive network to the primary network is below a certain threshold [2]. On one hand, the cognitive radio network (CRN) needs to mitigate the interference to satisfy the access precondition. On the other hand, it should try to maximize spectrum efficiency. Opportunistic power control (OPC) was proposed to optimize spectrum efficiency by making use of channel fading [3]. However, the performance of OPC is limited as it lacks the ability of interference cancellation.

Recently, the CRN with multiple antennas [multiple-input multiple-output (MIMO)] has received considerable attention as it can improve spectral efficiency and, at the same time, decrease the interference by exploiting the spatial degrees of freedom [4]. Due to its higher spectral efficiency, the multiuser MIMO (MU-MIMO) CRN has been a hot research topic [5]. Intuitively, for a MU-MIMO CRN, there are both internetwork and interuser interferences. Therefore, the key to realizing such a MU-MIMO CRN is minimizing the interuser interference subject to the internetwork interference constraint. In [6], the authors proposed an opportunistic spatial orthogonalization scheme, which selects the secondary users whose channels are orthogonal to the interference channel; hence, the internetwork interference is minimized. However, this scheme requires full interference channel state information (CSI) at the transmitter, which is quite difficult to realize in practical networks.

In general, a cognitive base station (CBS) is likely to obtain partial interference CSI by making use of channel reciprocity or through the aid of the primary network [7]. In addition, such CSI can be used by the CBS to design a robust transmission scheme, such as zero-forcing beamforming (ZFBF), to decrease both inter- and intranetwork interferences [8]. For MU-MIMO downlink, it is proved that ZFBF can achieve the asymptotically optimal performance with relatively low implementation complexity [9]. A limited feedback ZFBF scheme combined with adaptive power control is considered in a CRN to mitigate the interference [7], which shows that the more CSI at the transmitter, the higher the spectrum efficiency. Hence, in a MU-MIMO CRN, CSI is required for the transmitter to perform beamforming to reduce the inter- and intranetwork interferences. For the frequency-division duplexing (FDD) network, due to channel nonreciprocity, CSI should be fed back from the receiver to the transmitter. Considering that the feedback resource is quite limited in CRNs, it is desired to fulfill the performance requirement with a minimum feedback amount. Inspired by this, we propose to adaptively adjust the feedback amount, such that the performance of the MU-MIMO CRN can be optimized while meeting the interference constraint.

In addition, one of the challenging problems in CRNs is how to provide quality-of-service (QoS) guarantee for cognitive users (CUs), such as the delay requirement, while satisfying the given interference constraint to the primary network in a fading environment. Due to interference and spectrum limitations, it is impossible to provide QoS guarantee in a CRN by traditional means, such as increasing transmit power or adding transmission bandwidth. Hence, it is necessary to improve the performance by exploiting the other degrees of freedom. For example, the QoS constraint, such as delay, can be met by increasing the amount of feedback in a MIMO CRN [10].

Previous work shows that rateless coding can provide reliable delay guarantee for a CU while satisfying the interference constraint [11]. Inspired by this, we apply rateless coding into the MU-MIMO cognitive network with limited feedback. "Rateless" means the rate of code is not fixed before transmission [12]. The encoder generates the coded packets continuously according to a degree distribution until the original data are correctly recovered. The main advantages of the rateless-coded cognitive network are twofold. First, by making use of the property of rateless codes, it can provide delay guarantee for wireless services. Second, it reveals the intrinsic relationship between delay constraint and feedback amount, so that we can derive the required minimum feedback requirement for a given delay constraint. To our knowledge, we are the first to consider a rateless-coded MU-MIMO CRN by minimizing the total feedback amount while satisfying the interference constraint and the delay requirement, namely, maximizing the feedback efficiency. Our main contribution is to derive an efficient resource-allocation strategy, including transmit power control, transmission mode selection, and codebook size choice, according to the interference constraint, CSI, and QoS requirements.

The rest of this paper is organized as follows: In Section II, we provide a brief introduction of the considered rateless-coded MU-MIMO CRN. In Section III, we design the dynamic resource-allocation strategy. Then, several numerical results are presented in Section IV, and this paper is concluded in Section V.

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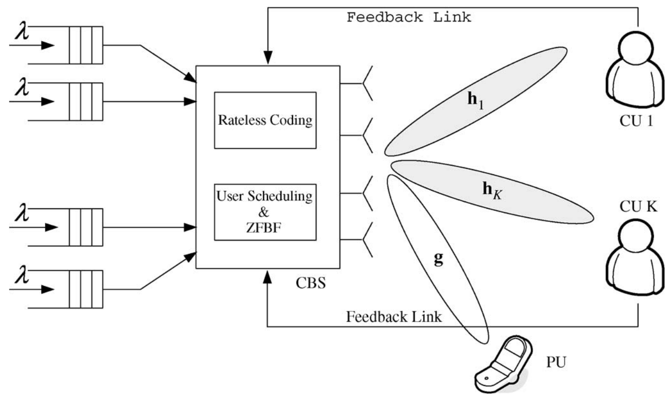

Fig. 1. Overview of the MU rateless-coded cognitive network.

II. System Model

We consider a homogeneous MU-MIMO CRN, including a CBS equipped with N_t antennas and K single-antenna CUs, as shown in Fig. 1. The cognitive network is allowed to access the spectrum licensed to the primary network only when the instantaneous interference to the primary user (PU) meets a given interference constraint. Considering that the average interference constraint (AIC) is more propitious to increase the capacity of the cognitive network than the peak interference constraint [13], [14], we also take the AIC as the accessing precondition of the cognitive network.

The data from the high layer are mapped into a sequence of frames. Following the previous analogous work [11], we model the frame arrival as a Poisson process with the average arrival rate λ for each CU. After rateless coding, the frame is mapped into an infinite number of coded packets for transmission over the channel. It is assumed that all CUs' channels $\mathbf{h}_k$ $(k = 1, \ldots, K)$ are independent and identically distributed (i.i.d.) complex Gaussian random vectors with zero mean and unit variance. At the beginning of each transmission period, each CU selects an optimal quantization codeword from its codebook $\mathcal{H}_k = \{\hat{\mathbf{h}}_{k,1}, \ldots, \hat{\mathbf{h}}_{k,2^B}\}$ of size 2^B according to the following codeword selection criteria:

$$i = \arg \max_{1 \le j \le 2^B} |\hat{\mathbf{h}}_{k,j}^H \tilde{\mathbf{h}}_k|^2 \tag{1}$$

where $\tilde{\mathbf{h}}_k = \mathbf{h}_k / \|\mathbf{h}_k\|$. Then, the CU conveys index i to the CBS. Based on the same quantization codebook, the CBS can recover the quantized channel information.

To control the interference from the CBS to the PU, the CBS must have interference CSI from the CBS to the PU. In this paper, we consider that the CBS has partial interference CSI by making use of channel reciprocity in the time-division duplexing system or through the aid of the PU in the FDD system. Following the common channel uncertain model [15], the relationship between the obtained and the actual interference CSI can be expressed as

$$\mathbf{g} = \sqrt{\kappa}\mathbf{g}_o + \sqrt{1-\kappa}\mathbf{n}_e \tag{2}$$

where $\mathbf{g}$ and $\mathbf{g}_o$ are the actual and the obtained interference CSI from the CBS to the PU, respectively. $\mathbf{n}_e$ is the CSI error with zero mean and unit variance complex Gaussian distributed entries, and it is independent of $\mathbf{g}_o$. κ is the correlation coefficient between $\mathbf{g}$ and $\mathbf{g}_o$. Large κ means the CBS has more interference CSI. For example, $\kappa = 1$ denotes that the CBS has full interference CSI.

Based on all the feedback information and partial interference CSI, the CBS constructs M transmit beams $\mathbf{w}_m$, $m = 1, \ldots, M$, by making use of the ZFBF design method, where M is the number of scheduled CUs for a transmission period, namely, the transmission mode. Specifically, assuming $\mathcal{M} = \{K_1, \ldots, K_M\}$ is the set of scheduled CUs for a certain period, for CU K_m, we first construct its complementary channel matrix

$$\bar{\mathbf{H}}_{K_m} = [\mathbf{g}_o, \hat{\mathbf{h}}_{K_1,\text{opt}}, \ldots, \hat{\mathbf{h}}_{K_{m-1},\text{opt}}, \hat{\mathbf{h}}_{K_{m+1},\text{opt}}, \ldots, \hat{\mathbf{h}}_{K_M,\text{opt}}]$$

where $\hat{\mathbf{h}}_{K_1,\text{opt}}$ is the optimal quantization codeword of CU K_1. Taking singular value decomposition (SVD) to $\bar{\mathbf{H}}_{K_m}$, if $\mathbf{V}_{K_m}^{\perp}$ is the matrix composed of the right singular vectors with zero singular values, then $\mathbf{w}_{K_m}$ is a normalized vector spanned by the space of $\mathbf{V}_{K_m}^{\perp}$. In other words, $\mathbf{V}_{K_m}^{\perp}$ is the null space of $\bar{\mathbf{H}}_{K_m}$, so that we have $\mathbf{g}_o^H \mathbf{w}_{K_m} = 0$ and $\hat{\mathbf{h}}_{K_u,\text{opt}}^H \mathbf{w}_{K_m} = 0$ for $K_u, K_m \in \mathcal{M}$, $u \neq m$. It is worth pointing out that to assure the existence of $\mathbf{V}_{K_m}^{\perp}$, M must be less than or equal to $N_t - 1$. Hence, the receive signal at the uth CU can be expressed as

$$\begin{aligned} y_u &= \sqrt{\frac{P}{M}} \sum_{m=1}^{M} \mathbf{h}_u^H \mathbf{w}_{K_m} x_{K_m} + n_u \\ &= \sqrt{\frac{P}{M}} \mathbf{h}_u^H \mathbf{w}_u x_u \\ &\quad + \sqrt{\frac{P}{M}} \sum_{m=1,\, K_m \neq u}^{M} \sqrt{a} \|\mathbf{h}_u\|^2 \mathbf{s}^H \mathbf{w}_{K_m} x_{K_m} + n_u \end{aligned} \tag{3}$$

where P is the total transmit power distributing to M CUs equally. x_{K_m} is the normalized transmit signal, and n_u is the zero mean and unit variance additive Gaussian white noise. Equation (3) follows from the fact that $\tilde{\mathbf{h}}_u = \sqrt{1-a}\hat{\mathbf{h}}_a + \sqrt{a}\mathbf{s}$ according to the theory of random vector quantization [16] and $\mathbf{h}_u^H \mathbf{w}_{K_m} = 0$, where $a = \sin^2(\angle(\tilde{\mathbf{h}}_k, \hat{\mathbf{h}}_k))$ is the magnitude of the quantization error, and $\mathbf{s}$ is a unit norm vector isotropically distributed in the null space of $\hat{\mathbf{h}}_k$ and is independent of a. Hence, the corresponding receive signal-to-interference-plus-noise ratio (SINR) can be cast as

$$\gamma_u = \frac{|\mathbf{h}_u^H \mathbf{w}_u|^2}{M/P + a \sum_{m=1,\, K_{m \neq u}}^{M} \|\mathbf{h}_u\|^2 |\mathbf{s}^H \mathbf{w}_{K_m}|^2}. \tag{4}$$

III. Adaptive Resource Allocation With Quality-of-Service Provisioning

Here, we focus on the design of an efficient adaptive resource-allocation strategy, including power control, mode, and codebook size selection, while satisfying the interference constraint and QoS requirement for the rateless-coded MU-MIMO CRN.

A. Rateless Coding in a MU-MIMO CRN

As mentioned earlier, the precondition that a cognitive network is allowed to access the licensed spectrum is that the interference to the PU satisfies the AIC. By making use of ZFBF, the residual instantaneous interference at the PU can be expressed as

$$\begin{aligned} I &= \frac{P}{M} L \sum_{m=1}^{M} |\mathbf{g}^H \mathbf{w}_{K_m}|^2 \\ &= \frac{P}{M} L \sum_{m=1}^{M} |\sqrt{1-\kappa}\mathbf{n}_e^H \mathbf{w}_{K_m}|^2 \end{aligned} \tag{5}$$

where L is the path loss, which is constant if the distance is given. Thus, the average residual interference can be expressed as

$$\begin{aligned} \bar{I} &= E\left[\frac{P}{M} L \sum_{m=1}^{M} |\sqrt{1-\kappa}\mathbf{n}_e^H \mathbf{w}_{K_m}|^2\right] \\ &= PL(1-\kappa) E\left[|\mathbf{n}_e^H \mathbf{w}_{K_m}|^2\right] \quad (6) \\ &= PL(1-\kappa) \quad (7) \end{aligned}$$

where (6) follows from the fact that $\mathbf{n}_e^H \mathbf{w}_{K_m}$ for all m are i.i.d. Equation (7) holds true because $\mathbf{n}_e^H \mathbf{w}_{K_m}$ is a complex Gaussian random variable with zero mean and unit variance. Hence, if the predetermined AIC is Γ, the CBS should perform the following power control:

$$P = \frac{\Gamma}{L(1-\kappa)}. \tag{8}$$

If the CBS has perfect interference CSI, namely, $\kappa = 1$, arbitrary power can be used because inter-network interference is completely canceled by ZFBF. With the increase of channel uncertainty, transmit power must be reduced accordingly to meet the AIC. Thus, transmit power P is determined as long as L and κ are known at the CBS. In fact, L and κ vary quite slowly; therefore, it is reasonable to assume that the CBS has full information about L and κ. Under this condition, the receive SINR at the uth CU is transformed as

$$\gamma_u = \frac{|\mathbf{h}_u^H \mathbf{w}_u|^2}{ML(1-\kappa)/\Gamma + a \sum_{m=1,\, K_m \neq u}^{M} \|\mathbf{h}_u\|^2 |\mathbf{s}^H \mathbf{w}_{K_m}|^2}. \tag{9}$$

For such an SINR, its cumulative distribution function is given by [17] as

$$F_{\gamma_u}(x) = 1 - \frac{\exp(-x/\rho)}{(1+\delta x)^{M-1}} \tag{10}$$

where $\rho = \Gamma/ML(1-\kappa)$ is the transmit SNR, and $\delta = 2^{-B/(N_t-1)}$.

At the uth CU, it performs hard decision to the receive rateless-coded packet. If the receive SINR is lower than a decision threshold η, we consider that the transmission is in outage, and a decision error occurs accordingly. Therefore, the probability that a rateless code packet is successfully received in the MU-MIMO CRN with limited feedback ZFBF can be expressed as

$$P_\eta = 1 - F_{\gamma_u}(\eta) = \frac{\exp(-\eta/\rho)}{(1+\delta\eta)^{M-1}}. \tag{11}$$

According to the property of rateless coding, for a frame consisting of G packets, if the CU receives N (slightly greater than G) coded packets correctly, the original frame can be decoded with a probability of 1 [19]. In other words, to receive N coded packets correctly, the CU needs to receive N/P_η coded packets on the average sense. Assuming the length of a transmission period is T and a coded packet occupies a period, the required transmission time for a frame is NT/P_η.

B. Relationship Among Network Parameters

In this paper, we adopt the round bin user-scheduling strategy, so that the access probability that a certain CU is scheduled is M/K. Combining the access probability and the successful receive probability, we can derive the serve rate as

$$\mu = \frac{MP_\eta}{KN} = \frac{M \exp\left(-\frac{\eta}{\rho}\right)}{KN\,(1+\delta\eta)^{M-1}}. \tag{12}$$

Given the arrival and serve processes, it is found that M/D/1 is applicable to characterize the focused scenario [18]. In this context, the average waiting delay for a certain CU is given by

$$D = \beta + \frac{\beta^2}{2(1-\beta)} \tag{13}$$

where $\beta = \lambda/\mu$. It is assumed that if the delay constraint is D_0, then we have

$$\beta^2 - 2(D_0+1)\beta + 2D_0 \geq 0. \tag{14}$$

By solving the preceding inequality and considering that only when $\beta < 1$, the queue is steady, we get

$$\beta \leq D_0 + 1 - \sqrt{D_0^2 + 1}. \tag{15}$$

Letting $\tilde{D}_0 = D_0 + 1 - \sqrt{D_0^2+1}$ and substituting (12) into (15), we have

$$\beta = \frac{KN\lambda(1+\delta\eta)^{M-1}}{M \exp\left(-\frac{\eta}{\rho}\right)} = \frac{KN\lambda\left(1+\eta 2^{-\frac{B}{N_{t-1}}}\right)^{M-1}}{M \exp\left(-\frac{\eta M g}{\Gamma}\right)} \leq \tilde{D}_0. \tag{16}$$

Hence, we reveal the intrinsic relationship between the network parameters, such as the number of CUs K, codebook size 2^B, transmission mode M and interference constraint Γ, and delay requirement D_0. Note that M has a complex impact on the delay. This is because a large M means a high access probability, but a large interuser interference. If the interference constraint is quite loose, namely, $\Gamma \to \infty$, then the CBS can use its maximum transmit power $P_{\max}$; thus, we have

$$\beta = \frac{KN\lambda\left(1+\eta 2^{-\frac{B}{N_{t-1}}}\right)^{M-1}}{M \exp\left(-\frac{\eta M}{P_{\max}}\right)}$$

which is equivalent to a general MU limited feedback ZFBF network. In a practical cognitive network, the interference constraint may be relatively strict. In this context, the CBS can meet the delay requirement by decreasing K, increasing B, or selecting an optimal M.

C. Optimization Problem Formulation

Considering that the spectrum is the most scarce resource in a cognitive network, it is expected to meet the interference constraint and delay requirement with the minimum feedback resource. It is noticed that the total feedback amount $\zeta = MB$ is jointly determined by transmission mode and codebook size. Thereby, we take the minimization of ζ while satisfying the interference constraint and delay requirement as the optimization objective, and the problem searching for optimal transmission mode M and codebook size 2^B is equivalent to the following optimization problem:

$$J_1 : \min_{M,B} \quad \zeta = MB \tag{17}$$

$$\text{s.t.} \quad \frac{KN\lambda\left(1+\eta 2^{-\frac{B}{N_{t-1}}}\right)^{M-1}}{M \exp\left(-\frac{\eta M g}{\Gamma}\right)} \leq \tilde{D}_0 \tag{18}$$

$$2 \leq M \leq N_{t-1} \tag{19}$$

$$M \leq K \tag{20}$$

$$B \leq B_0 \tag{21}$$

where (18) includes interference and delay constraints, (19) and (20) are the constraints of transmission mode due to the spatial degrees of freedom, and (21) is the constraint on codebook size by considering the design of practical quantization codebook. It is worth pointing out that we let $M \geq 2$ because $M = 1$ does not belong to ZFBF any more. Since M and B are both integers, J_1 is an integer programming problem; hence, it is difficult to obtain the closed-form expression of the optimal M and B. Examining (18), it is found that the delay is a decreasing function of B. When given a transmission mode M, we could find the smallest B_M satisfying constraint (18). If $B_M \leq B_0$, it is optimal under this condition; otherwise, there is no feasible B. For each M from 1 to N_t, we could derive the corresponding optimal codebook size. Among all (B, M) combinations, it is easy to get the optimal one with the smallest total feedback amount. Thus, we propose Algorithm 1.

Algorithm 1

1) Initialization: given N_t, N, K, B_0, $\tilde{D}_0$, λ, η, L, κ, and Γ. Set $M = 2$ and $i = 1$.
2) Compute B^* satisfying

$$\frac{KN\lambda\left(1+\eta 2^{-\frac{B}{N_t-1}}\right)^{M-1}}{M\,\exp\left(-\frac{\eta M g}{\Gamma}\right)} = \tilde{D}_0.$$

If $\lceil B^* \rceil \leq B_0$, then let $M_i = M$, $B_i = \lceil B^* \rceil \leq B_0$, and $i = i+1$, where $\lceil B^* \rceil$ is the smallest integer not less than B^*.
3) If $M + 1 \leq N_t - 1$, then $M = M + 1$ and go to 2).
4) Search $j^* = \arg\min_{1 \leq j \leq i} M_j B_j$. M_{j^*} and $2^{B_{j^*}}$ are the optimal transmission mode and codebook size, respectively.

Clearly, Algorithm 1 is essentially a numerical searching method. If the antenna number at the CBS N_t is not large, such as $N_t = 4$ for the Long-Term Evolution system, it is an appealing method to derive the optimal (M, B) for the rateless-coded MU-MIMO CRN with delay constraint. However, if N_t is relatively large in some cases, Algorithm 1 may not be feasible. Herein, we give a suboptimal algorithm with low complexity to derive the (M, B) combination. As mentioned earlier, one of the difficulties to solve the aforementioned problem lies in that both M and B are integers. If we allow M and B to be real numbers, we may reduce the solving complexity. In this context, J_1 is transformed as the following general optimization problem:

$$J_2 : \min_{M,B} \quad \zeta = MB \tag{22}$$

$$\text{s.t.} \quad (18), (19), (20), (21) M \in \mathbf{R}^+ \tag{23}$$

$$B \in \mathbf{R}^+ \tag{24}$$

where $\mathbf{R}^+$ is the collection of positive real values. J_2 can be easily solved by some optimization software, such as *Lingo*. It solves such a nonlinear programming problem by sequential linear programming (SLP). SLP consists of linearizing the objective and constraints in a region around a nominal operating pointing by a Taylor series expansion. The resulting linear programming problem is then solved by standard methods such as the interior-point method. Thus, the complexity of Algorithm 2 depends on the partition of the linear region and the complexity of the interior-point method. In general, if the number of transmission modes $N_t - 2$ is large, Algorithm 2 has relatively lower complexity. Assuming $(M^\dagger, B^\dagger)$ is the optimal solutions to J_2. Let $M_1 = \lceil M^\dagger \rceil$ and $M_2 = \lfloor M^\dagger \rfloor$ be the candidate transmission modes, and let $B_1 = \lceil B^\dagger \rceil$ and $B_2 = \lfloor B^\dagger \rfloor$ be the candidate feedback amounts. Then, select the combination from (M_1, B_1), (M_1, B_2), (M_2, B_1), and (M_2, B_2) that has the smallest total feedback amount while meeting constraint (18). In the rest of this paper, we name this suboptimal algorithm as Algorithm 2.

Remark: To find the optimal solution of an optimization problem, the feasible set must be nonnull. However, if the delay constraint is too strict, even with $B = B_0$, there may not be an M that satisfies (18) and (20). In this case, we should decrease K. In other words, given the constraints, there is an upper bound of the number of admissible CUs.

TABLE I
OPTIMIZATION RESULTS OF TRANSMISSION MODE AND FEEDBACK AMOUNT WITH DIFFERENT K AND φ

		φ(dB)	0.5	1.0	1.5	2.0	2.5
$K = 7$	Algorithm 1	M	2	2	2	2	2
		B	3	1	1	1	1
	Algorithm 2	M	2	2	2	2	2
		B	3	1	1	1	1
$K = 8$	Algorithm 1	M	3	3, 2	2	2	2
		B	6	4, 6	3	2	1
	Algorithm 2	M	3	3, 2	2	2	2
		B	6	4, 6	3	2	1
$K = 9$	Algorithm 1	M	3	3	3	3	3
		B	7	7	5	3	2
	Algorithm 2	M	3	3	3	3	3
		B	7	7	5	3	2

IV. SIMULATION RESULTS

To examine the effectiveness of the proposed feedback-efficient ZFBF scheme in a rateless-coded MU-MIMO CRN with delay constraint, we present some numerical results in different scenarios. For all scenarios, we set $N_t = 4$ $L = 128$, $N = 135$, $\lambda = 0.001$, $\eta = 0.3$, $T = 0.01$ ms, $B_0 = 8$, and $D_0 = 0.1$ ms. We use Algorithms 1 and 2 to denote the proposed optimal and suboptimal methods, respectively, and let $\varphi = \Gamma/L(1-\kappa)$.

Table I shows the optimization results of transmission mode M and feedback amount B by the optimal and suboptimal algorithms with different K and φ when $D_0 = 0.1$ ms. It is found that the two algorithms have the same optimization results in all scenarios, so that we could replace Algorithm 1 with Algorithm 2 in a practical network. Given φ, namely, the transmit SNR of the CBS, with the increase of K, B first increases accordingly and then M increases gradually. This is because a larger B can reduce interuser interference and then the addition of M can support more CUs with delay requirement. On the other hand, given K, with the increase of φ, B first decreases and then M also decreases in sequence. This is because M has a greater impact on delay than B. If M decreases, the access probability becomes smaller accordingly; hence, the transmission of coded packets will take longer time, leading to a large delay. In addition, it is shown that the optimization results may not be unique in some scenarios. For example, when $K = 8$ and $\varphi = 1$ dB, $(M = 3,\ B = 4)$ and $(M = 2,\ B = 6)$ can satisfy all the constraints and have the same total feedback amount, so that they are both optimal in the sense of feedback efficiency.

Table II gives the optimization results of transmission mode M and feedback amount B by the optimal and suboptimal algorithms with different D_0 and φ when $K = 7$. It is reconfirmed that the two algorithms can obtain the same results. In the case with strict delay and interference constraints, i.e., $D_0 = 0.03$ ms and $\varphi = 0.5$ dB, the CBS should use low power to decrease the interference to the PU. On the other hand, the CBS needs to improve the rate to satisfy the delay constraint. Thereby, the CBS adopts a high transmission mode to reduce the waiting duration of each CU and uses a large feedback amount to decrease interuser interference. With loose delay constraints (e.g., $\varphi = 0.5$ dB, see the fourth column in Table II), the CBS first reduces the feedback amount because the interuser is quite small under the condition of strict interference constraint or low transmit power; therefore, it makes no sense to further decrease the interuser interference by using a large feedback amount. Then, the transmission mode is also reduced to minimize the total feedback amount.

TABLE II
OPTIMIZATION RESULTS OF TRANSMISSION MODE AND FEEDBACK AMOUNT WITH DIFFERENT N_t AND φ

		φ(dB)	0.5	1.0	1.5	2.0	2.5
$D_0 = 0.03$ms	Algorithm 1	M	3	3	3	2	2
		B	6	4	2	2	1
	Algorithm 2	M	3	3	3	2	2
		B	6	4	2	2	1
$D_0 = 0.05$ms	Algorithm 1	M	3	2	2	2	2
		B	4	3	1	1	1
	Algorithm 2	M	3	2	2	2	2
		B	4	3	1	1	1
$D_0 = 0.10$ms	Algorithm 1	M	2	2	2	2	2
		B	3	1	1	1	1
	Algorithm 2	M	2	2	2	2	2
		B	3	1	1	1	1

V. CONCLUSION

A major contribution of this paper is the design of adaptive resource allocation for a rateless-coded MU-MIMO CRN to provide a feedback-efficient and delay-guaranteed service. By making use of the property of rateless code, we derived the intrinsic relationship between the network parameters and the delay requirement while satisfying the interference constraint. We formulated an optimization problem to minimize the total feedback amount and derived the optimal transmission mode and codebook size for a given network condition with imperfect interference CSI at the CBS. We also provided a heuristic algorithm that can derive an optimal solution for a practical network. Results show that our adaptive resource-allocation strategy can dynamically adjust the feedback amount, transmit power, and transmission mode to meet the delay requirements while keeping the interference to the PU under control.

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Estimation of Constrained Capacity and Outage Probability in Lognormal Channels

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***Abstract*—The driving force behind this work is the desire to obtain one method for estimating the ergodic capacity of lognormal (LN) channels for both Shannon capacity and constrained capacity. In recent years, researchers have determined methods for calculating the ergodic Shannon capacity for LN channels. However, in practical communication systems, the input signal is constrained to a discrete signaling set such as finite-size quadrature amplitude modulation constellations. At a high SNR, the Shannon capacity greatly overestimates the capacity of these practical systems, particularly for low-order constellations. For this reason, a method is needed to evaluate the capacity and outage probability for LN channels when the signal set is constrained to a finite alphabet. The main contribution of this paper is the introduction of a simple but accurate method for calculating both the ergodic Shannon capacity and the ergodic constrained capacity of practical signals for LN channels. This method also facilitates straightforward computation of outage probability and outage capacity. Prior to this work, the ergodic constrained capacity, outage probability, and outage capacity of practical signals for LN channels had not been dealt with in the literature.**

***Index Terms*—Constrained capacity, fading channels, lognormal (LN) distribution.**

I. INTRODUCTION

The lognormal (LN) distribution is often used in wireless communications to model midscale fading caused by shadowing in outdoor environments. More recently, it has been also applied to describe

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