Compressive Random Access With Multiple Resource Blocks and Fast Retrial

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Abstract—In this paper, we propose a compressive random access (CRA) scheme using multiple resource blocks (RBs) to support massive connections for machine type communications. The proposed CRA scheme is scalable. As a result, if the number of devices increases, more RBs can be added to support them. Thanks to multiple RBs, we can employ fast retransmission to reduce collisions and improve the throughput. In CRA, the number of RBs can be added in advance at a receiver. In CRA, spreading codes are not necessarily orthogonal due to MUD that can detect multiple signals in the presence of interference. Consequently, the main advantage of CRA over conventional multichannel random access schemes is the increase of the number of channels that can reduce the probability of collision and improve the throughput at the cost of increased complexity at a receiver. In addition, CRA supports grant-free transmissions. Thus, as in [16], grant-free CRA can be more efficient than grant-based schemes since it does not need to wait for the grant from an access point (AP).

Grant-free CRA schemes can be characterized by a unique signature sequence for each device. Thus, the number of devices becomes limited by the number of signature sequences. To support many devices in MTC, although wide bandwidth is considered, this can result in two difficulties: (i) a long sequence is required to accommodate a number of devices with sparse activity; (ii) the complexity of CS algorithms for MUD can be high due to a large number of columns (or signature vectors) in a measurement matrix (a high computational complexity). To avoid the above difficulties, we can apply the approach used in the RACH procedure to grant-free CRA. That is, instead of assigning a unique signature to each device, a randomly selected signature from a pool of predetermined signatures can be used when an active device is to transmit signals to a receiver or AP, where a signature code is used as a spreading code to transmit data symbols as in CRA.

In this paper, we generalize the CRA scheme in [22] using multiple resource blocks (RBs) in a multicarrier system with a certain re-transmission strategy. In the proposed scheme, we divide subcarriers into multiple groups, or RBs, so that it becomes scalable, since more RBs can be added to support more devices in MTC. At the AP, parallel multiple CS-based detectors can be applied to exploit the sparsity of active devices for multiuser detection (MUD) in random access.

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employed for MUD with low complexity. In addition, thanks to multiple RBs, we can employ fast retrial [23] between RBs for re-transmissions of collided packets. In fast retrial, when a device experiences collision in the current time slot, this device can re-transmit in the next time slot without random backoff. As a result, the access delay can be short. In summary, the main advantage of the proposed CRA scheme over other grant-free CRA schemes (with single big RB) [12], [14]–[16] is mainly three-fold: i) scalability; ii) a low computational complexity for CS based MUD; iii) fast retrial between RBs for short access delay. The main contributions1 of the paper can also be summarized as follows: a) a scalable grant-free CRA scheme is proposed not only to support a large number of devices with a reasonably low complexity for CS based MUD, but also to accommodate fast retrial; b) the stability and steady-state performance are analyzed under certain assumptions to see the impact of the number of RBs as well as other parameters on the performance of the proposed CRA scheme.

The rest of the paper is organized as follows. In Section II, we present a system model for CRA with multiple RBs in a multicarrier system. We discuss CS based MUD in Section III and propose a model for its recovery performance in CRA. With a rate control scheme, we analyze the stability of the proposed CRA scheme with fast retrial in Section IV. To understand the throughput and access delay, we study a steady state analysis in Section V. In Section VI, simulation results are presented with theoretical results obtained from Section V. We finally conclude the paper with some remarks in Section VII.

Notation: Matrices and vectors are denoted by upper- and lower-case boldface letters, respectively. The superscripts (T) and (H) denote the transpose and complex conjugate, respectively. E[·] and Var(·) denote the statistical expectation and variance, respectively. \( \mathcal{C}(\alpha, \mathbf{R}) \) represents the distribution of circularly symmetric complex Gaussian (CSCG) random vectors with mean vector \( \alpha \) and covariance matrix \( \mathbf{R} \).

II. SYSTEM MODEL

Consider uplink transmissions from a number of devices to an AP. Suppose that when a device becomes active to transmit a packet, it can transmit its packet without any permission (i.e., grant-free transmissions are assumed) [16]. For uplink transmissions, a radio resource block is divided into \( M \) RBs and each RB is orthogonal to each other. In each RB, there are \( N \) spreading codes (SCs) of length \( L \). For grant-free CRA, an active device is to randomly choose an RB and an SC for data transmissions. Throughout the paper, we assume a multicarrier system that has \( J = LM \) subcarriers. Thus, an RB consists of \( L \) subcarriers and each SC is a multicarrier spread sequence of length \( L \) [25]. In Fig. 1, we illustrate multiple RBs with \( J \) subcarriers in the frequency domain.

Let \( \mathbf{C} = [\mathbf{c}_0, \ldots, \mathbf{c}_{N-1}] \) denote a matrix of \( N \) SC vectors where \( \mathbf{c}_n \) denotes the \( n \)th SC, which is a multicarrier spread sequence of length \( L \). Thus, the size of \( \mathbf{C} \) becomes \( L \times N \), and

1Note that multiple RB based CRA has been studied in [24]. However, in [24], no re-transmission is considered (this paper is an extension of [24]).

2In the paper, we assume that the length of packet is equivalent to the length of time slot.

\[ y_{m,t} = [y_{m,t,0}, \ldots y_{m,t,L-1}]^T = \mathbf{C}s_{m,t} + \mathbf{n}_{m,t}, \quad t = 0, \ldots, T - 1, \]

which is referred to as the virtual bandwidth expansion factor. Note that if SC sequences are orthogonal to each other, we have \( \eta = 1 \) (i.e., \( N = L \)). We assume the same set of SC sequences for all RBs.

Suppose that a packet consists of \( T \) symbols and each active device can choose one of \( M \) RBs uniformly at random. At the AP, the received signal vector at (symbol) time \( t \) over the \( m \)th RB is given by

\[ s_{m,t} = \sum_{k \in \mathcal{K}_{m,n}} h_{k,m} x_{k,t}, \]

where \( h_{k,m} \) denotes the (frequency-domain) channel coefficient from device \( k \) to the AP over the \( m \)th RB and \( x_{k,t} \) represents the signal from device \( k \) at time \( t \). In (2), we assume that the bandwidth of an RB is sufficiently narrow so that the frequency-domain channel gain remains unchanged within the bandwidth of an RB. The total number of active devices is given by

\[ K = \sum_{m=1}^{M} \sum_{n=1}^{N} |\mathcal{K}_{m,n}| \]

and the number of active devices that choose the \( m \)th RB is given by

\[ K_m = \sum_{n=1}^{N} |\mathcal{K}_{m,n}|. \]

In general, we have \( K_m \ll N \) due to sparse activity.

For convenience, the above random access system with multiple RBs (i.e., \( M > 1 \)) is referred to as the multiple RB (MRB) based CRA (MRB-CRA) system in this paper. In addition, we employ fast retrial [23] between RBs to re-transmit collided packets for short access delay. That is, if an active device has a collided packet, this packet can be immediately re-transmitted in the next time slot2 through a randomly selected RB among \( M \) RBs.

Fig. 1. An illustration of multiple RBs in the frequency domain.
It is noteworthy that the resulting system becomes scalable. Thus, if the number of devices increases, we can add more RBs, which of course increases the system bandwidth as shown in Fig. 1. In addition, at an AP, there can be $M$ parallel MUDs to recover sparse signals in each RB. This feature might be important to reduce the processing time at the AP since the total processing time becomes identical to the processing time of MUD for one RB if a parallel processor is used to implement the receiver [24].

Although we assume that an RB is selected uniformly at random in this paper, it is also possible to choose it based on the channel state information (CSI) at each active device to lower the transmission power. In (2), we need to adjust the amplitude of $x_{k,t}$ to overcome fading if the channel gain, $|h_{k,m}|$, is low. In general, each device can choose the amplitude of $x_{k,t}$ to be inversely proportional to the channel gain to equalize the overall signal gain. In this case, if $|h_{k,m}|$ is low, the transmit power has to be high, which is not desirable. In the MRB-CRA system, this problem can be mitigated if an active device can choose the RB of the highest channel gain. That is, active device $k$ can choose the RB as follows: $m(k) = \arg\max_m |h_{k,m}|$, where $m(k)$ denotes the index of the selected RB by active device $k$. Since the channel gains are random, the selection of RBs by active devices becomes also random and active devices could be uniformly distributed over multiple RBs in this case as well (provided that $h_{k,1}, \ldots, h_{k,M}$ are iid). From this, throughout the paper, we assume that the power control is adopted to equalize the overall signal gain as follows:

\[
|h_{k,m(k)}x_{k,t}| = \sqrt{P}, \quad \text{for all active device } k,
\]

where $P$ is the transmit power. Thus, the signal to noise ratio (SNR) becomes $\text{SNR} = \frac{P}{\sigma^2}$. Throughout the paper, we assume that the SNR is sufficiently high. Note that a similar approach is considered in [26], where the phase of the signal is also compensated.

III. CS BASED MUD

In this section, we focus on CS based MUD for one RB (as each RB has the same structure) to recover multiple signals and propose a model for the performance analysis.

A. CS Based Signal Recovery

For convenience, since we consider one RB, we omit the RB index $m$ if there is no risk of confusion. Let $Y = [y_0 \ldots y_{T-1}]$, $S = [s_0 \ldots s_{T-1}]$, and $N = [n_0 \ldots n_{T-1}]$. Then, (1) becomes

\[
Y = CS + N. \tag{3}
\]

Let $I$ denote the support of $s_t$. If $C$ is seen as a measurement matrix, the estimation of $I$ from $Y$ in (3) is a typical multiple measurement vectors (MMV) problem [27] [28] as the support of $s_t$ is the same for all $t$. Under the high SNR assumption or ignoring $N$, the MMV sparse recovery problem can be formulated as follows [28]:

\[
\hat{S} = \arg\min_S |\text{supp}(S)| \quad \text{subject to } CS = Y, \tag{4}
\]

where $\text{supp}(S)$ represents the support of matrix $S$, which is defined by $\text{supp}(A) = \bigcup_i \text{supp}(a_i)$. Here, $a_i$ denotes the $i$th column vector of $A$. In this case, a sufficient and necessary condition to estimate $I$ [27], [28] is given by

\[
N < \frac{\text{spark}(C) - 1 + \text{rank}(S)}{2}, \tag{5}
\]

where $\text{spark}(C)$ is the smallest number of columns from $C$ that are linearly dependent [29]. It can be readily shown that $\text{rank}(S) \leq \min\{N, T\}$. Since each element of $S$ is iid, we have $\text{rank}(S) = N$ if $T \geq N$ with probability (w.p.) 1. From this, (5) is reduced to

\[
N \leq D = \text{spark}(C) - 2, \tag{6}
\]

where $D$ is the sparsity threshold for a recovery guarantee. If $C$ is random (e.g., all the elements of $C$ are independent CSCG random variables) and $K \geq L$, $\text{spark}(C) - 1 = \text{rank}(C) = L$ w.p. 1 [30]. In this case, we have

\[
D = L - 1. \tag{7}
\]

However, in practice, the sparsity threshold might be smaller than $L - 1$ due to various reasons. For example, for low-complexity implementations, greedy algorithms can be used, which result in suboptimal performances. In addition, due to the background noise, there might be performance degradation.

B. A Model for Recovery Performance

Throughout the paper, we assume that the AP is able to recover the signals of up to $D$-sparsity in each RB, where $D < L$. That is, we consider the following assumptions.

A1 If the number of active devices in an RB is greater than $D$, the AP cannot recover them at all.

A2 If the number of active devices in an RB is less than or equal to $D$, the AP recovers the active devices whose SCs do not collide with each other.

Clearly, $D$ is a threshold value and depends on the properties of $C$ including its size, i.e., $N$ and $L$. Note that although there are more than $D$ active devices, the AP may be able to recover some of them. However, for tractable analysis, we simply assume A1. In A2, it is assumed that although the AP can recover all the signals, it cannot resolve collided signals from the devices that choose the same SC. In general, in this paper, $D$ is seen as a performance indicator of CS based MUD to be estimated.

Based on the assumptions of A1 and A2, when there are $K_m$ active devices in RB $m$, since there are $N$ SCs per RB, the average number of unsuccessful devices becomes

\[
U(K_m) = \begin{cases} 
K_m - K_m \left(1 - \frac{1}{N}\right)^{K_m - 1}, & \text{if } K_m \leq D; \\
K_m, & \text{if } K_m > D. 
\end{cases} \tag{8}
\]

In Fig. 2, we show the average number of unsuccessful devices, i.e., $U(K_m)$ when the simultaneous orthogonal matching pursuit (S-OMP) algorithm proposed in [27] [31] is used for CS based MUD. Here, for simulations, we assume that each element of $C$ is an independent CSCG random variable with zero mean and variance $\frac{1}{C}$. It is shown that $U(K_m)$ from the simulation results follows $K_m - K_m \left(1 - \frac{1}{N}\right)^{K_m - 1}$ when $K_m$ is small. However,
as $K_m$ approaches a certain value, $U(K_m)$ increases rapidly. Thus, the model in (8) can be used to analyze the performance of MRB-CRA, where we assume that there exists a threshold value $D$ such that $U(K_m) = K_m$ if $K_m > D$ (i.e., A1).

Note that according to Figs. 2(a) and (b), $D$ might be dependent on $L$. For example, when $L = 32$, as shown in Fig. 2(a), we can say $D \approx 0.6L$, while $D \approx 0.8L$ when $L = 64$ according to Fig. 2(b). Furthermore, $D$ also depends on the SNR. In addition, as mentioned earlier, although $K_m > D$, it is also possible that some signals can be recovered as shown in Fig. 2. If a better recovery algorithm is used, we expect to have a larger $D$, which results in a better performance. In [32], the performances of different algorithms can be found, while we only consider S-OMP (for simulations) in this paper.

In Fig. 2, we also show the number of unsuccessful devices of conventional multichannel ALOHA, which is given by $U_{\text{aloha}}(K_m) = K_m - K_m(1 - \frac{1}{T})^{K_m-1}$, where each RB has only $L$ (not $N$) orthogonal SCs. In conventional multichannel ALOHA, it is not necessary to use CS based MUD due to orthogonal SCs. That is, a bank of correlators can be used to recover multiple signals. Although there is no interference, due to a smaller number of channels (not $N$, but $L$), the probability of collision is higher than that of CRA. As a result, as shown in Fig. 2, the performance of conventional multichannel ALOHA would be worse that that of CRA. From this, we can claim that the advantage of CRA over conventional multichannel ALOHA is a low probability of collision thanks to an increased number of (non-orthogonal virtual) channels (from $L$ to $N$) at the cost of high recovery complexity at a receiver. Note that as we only consider S-OMP in this paper, it might be useful to consider the computational complexity of S-OMP. Since S-OMP is a greedy algorithm [31] [11], its computational complexity is not significantly high, which is mainly $O(cL^2 + N)$ per RB, where $c > 1$ is a constant. On the other hand, the complexity per RB at a receiver in conventional multichannel ALOHA might be $O(L^2)$.

It is important to note that the receiver complexity of MRB-CRA with S-OMP decreases with $M$ when $J$ is fixed. Since the total computational complexity is $O(M(cL^2 + \eta L)) = O(cL^2 + \eta J)$, we can clearly see that a large $M$ (or more RBs) is desirable for a low computational complexity. However, as shown in Fig. 2, if $L$ decreases, $\frac{Q}{c}$ tends to decrease, which degrades the recovery performance. Thus, we can see that there might be a trade-off between the performance and complexity (this will be confirmed by simulations in Section VI).

IV. STABILITY ANALYSIS WITH FAST RETRIAL

In [23], for multichannel ALOHA, a re-transmission strategy which is called fast retransmission is proposed, where a collided packet is re-transmitted at the next slot without any random backoff delay thanks to the existence of multiple channels. Since we assume multiple RBs for CRA, i.e., MRB-CRA, fast retransmission can be employed as a re-transmission strategy for collided SCs as mentioned in Section II. In this section, we study the stability of MRB-CRA with fast retransmission.

Suppose that a device experiencing SC collision attempts re-transmission in the next slot based on fast retransmission [23]. For re-transmission, the device chooses an RB among $M$ RBs and an SC within the selected RB uniformly at random. There are also new active devices. For convenience, let $A_m(q)$ denote the number of new active devices to RB $m$ at time slot $q$. Here, $q$ is used for the time slot index. Thus, $K_m(q)$ is a sum of the numbers of new packets and re-transmitted packets, where $K_m(q)$ represents the number of active devices transmitting packets to RB $m$ at time slot $q$. Throughout the paper, we consider an

3In order to increase the number of channels for a high throughput in multichannel ALOHA, non-orthogonal SCs can be used. In this case, a bank of correlators cannot be used at a receiver due to interference and a CS based MUD approach needs to be used as in [12], [33], which results in CRA. Thus, by conventional multichannel ALOHA, we mean multichannel ALOHA with $L$ orthogonal channels in this paper.
4We assume that packets and active devices are interchangeable in this section as an active device transmits a packet.
independent Poisson random variable for \( A_m(q) \) as follows:

\[
\Pr(A_m(q) = n) = \frac{\lambda^ne^{-\lambda}}{n!},
\]

(9)

where \( \lambda \) is the arrival rate per RB, i.e., \( A_m(q) \sim \text{Pois}(\lambda) \). Here, \( \text{Pois}(\lambda) \) denotes the distribution of a Poisson random variable with mean \( \lambda \).

In fast retrial, thanks to multiple RBs, we consider the following rate control strategy.

**A3** If \( K_m(q) > \bar{K} \), the AP informs the devices not to send any new packets, where \( \bar{K} \) is a pre-determined threshold.

This rate control strategy is necessary to avoid the growth of \( K_m(q) \) so that the access delay cannot be arbitrarily long. Note that there can be other rate control strategies. However, for simplicity, we only consider A3. According to A3, the AP needs to broadcast the binary signals that inform the states of RBs (whether or not \( K_m(q) \) is greater than \( \bar{K} \)). Thus, at the beginning of each (uplink) time slot, there should be a broadcast signal of \( M \) bits from the AP to devices for the rate control.

Let \( k(q) = [K_1(q), \ldots, K_M(q)]^T \). Under the assumptions of A1 and A2, we define the number of unsuccessfully recovered packets in RB \( m \) at time slot \( t \) as

\[
[K_m(q)]_D = \begin{cases} 
K_m(q), & \text{if } K_m(q) > D; \\
i, & \text{if } K_m(q) \leq D \text{ w.p. } \beta(K_m(q), n),
\end{cases}
\]

(10)

where \( \beta(K_m, i) \) represents the probability that there are \( i \) collided SCs when there are \( K_m \leq N \) packets and each packet independently chooses one among \( N \) SCs. Clearly, \( [K_m(q)]_D \) is a random variable.

With fast retrial, the unsuccessfully recovered packets are scheduled to re-transmit in the next time slot. The number of re-transmitted packets from RB \( m \) at time slot \( q \) to RB \( l \) at time slot \( q + 1 \) is denoted by \( R_m,l(i) \), where \( i \) represents the number of unsuccessfully recovered packets in RB \( m \) at time slot \( q \). Then, the total number of packets in RB \( m \) at time slot \( q + 1 \) can be expressed as

\[
K_m(q + 1) = \sum_{l=1}^{M} R_{m,l}([K_l(q)]_D) + \tilde{A}_m(q + 1), \tag{11}
\]

where

\[
\tilde{A}_m(q + 1) = \begin{cases} 
A_m(q + 1), & \text{if } K_m(q) > \bar{K}; \\
0, & \text{o.w.}
\end{cases}
\]

(12)

Note that (12) is due to the rate control of A3. From (11) and (12), we can see that \( k(q) \) becomes a Markov process. We derive a sufficient condition for stability as follows.

**Theorem 1:** Let \( \tilde{A}_m = \mathbb{E}[A_m(q)] \). With the rate control of A3, if

\[
\tilde{A}_m = \lambda < B_{D,N} \triangleq D \left( 1 - \frac{1}{N} \right)^{D-1}, \text{ for all } m, \tag{13}
\]

then \( k(q) \) is positive recurrent.

**Proof:** See Appendix A.

In (13), it is noteworthy that \( B_{D,N} \approx D \) if \( N \gg D \). This indicates that the new arrival rate per RB is to be less than \( D \) for stable MRB-CRA when \( N \gg L > D \). This indicates that the estimation of \( D \) plays a crucial role in MRB-CRA with fast retrial.

**V. PERFORMANCE ANALYSIS OF MRB-CRA**

In this section, in order to find the throughput and delay of MRB-CRA, we consider a steady state analysis with a receiver that is capable of recovering \( D \) multiple signals.

**A. A Steady State Analysis**

In general, the throughput analysis of MRB-CRA with fast retrial is not easy due to the interaction between multiple RBs in terms of numbers of the packets to be re-transmitted. That is, \( K_m(q + 1) \) depends on \( K_l(q), l = 1, \ldots, M \), as shown in (11). To avoid this difficulty, in the steady state, we assume that the number of packets to be re-transmitted (or collided packets in the previous time slot) in each RB is an independent Poisson random variables with mean \( \lambda_2 \), i.e.,

\[
\sum_{l=1}^{M} R_{m,l}([K_l(q)]_D) \sim \text{Pois}(\lambda_2), m = 1, \ldots, M,
\]

where \( \lambda_2 = \mathbb{E}[\sum_{l=1}^{M} R_{m,l}([K_l(q)]_D)] \). Clearly, this assumption is not true. However, if \( M \) is sufficiently large, it might be a reasonable approximation such as the Kleinrock independence approximation [34] [7].

Suppose that the arrival rate is sufficiently low so that \( \tilde{A}_m(q) = A_m(q) \) for all \( q \), i.e., the rate control of A3 is hardly imposed. Although this is an approximation, we assume this for tractable analysis (i.e., the approximation allows us to simplify the analysis, while simulation results in Section VI show that this approximation is reasonable). Since the packets to be re-transmitted are to be re-allocated to the RBs uniformly at random, from (11), we assume that \( K_m(q + 1) \) becomes a Poisson random variable\(^5\) with mean \( \lambda + \lambda_2 \). For convenience, let

\[
\lambda_1 = \lambda + \lambda_2, \tag{14}
\]

which is the average number of packets to be transmitted per RB as illustrated in Fig. 3.

\(^5\)Since the sum of two independent Poisson random variables with means \( \lambda_a \) and \( \lambda_b \) is a Poisson random variable with the mean \( \lambda_a + \lambda_b \), we can assume that \( K_m(q + 1) \) is also a Poisson random variable.
Theorem 2: Suppose that $K_m(q) \sim \text{Pois}(\lambda_1)$. Under A1 and A2, $\lambda_2$ can be given by

$$\lambda_2 = \lambda_1 \left(1 - e^{-\lambda_1} \frac{\Gamma(D, \nu_1)}{(D-1)!}\right), \quad (15)$$

where $\nu_1 = \lambda_1 \left(1 - \frac{1}{\nu} \right)$ and $\Gamma(d, x) = \int_x^{\infty} e^{t-k}d^{-1}dt$ is the upper incomplete gamma function.

Proof: See Appendix B.

To satisfy (14) and (15), we can show that $\lambda$ has to be bounded as

$$\lambda \leq \lambda_{\text{max}} = \max_{\lambda_1} \lambda_1 e^{-\lambda_1} \frac{\Gamma(D, \nu_1)}{(D-1)!}, \quad (16)$$

where $\lambda_{\text{max}}$ denotes the maximum of $\lambda$. In addition, denote by $\lambda_1$ the solution to (16). Clearly, if $\lambda$ is less than or equal to $\lambda_{\text{max}}$, the steady state solution that satisfies (14) and (15) exists.

Since $e^{-\lambda_1/N} < 1$, from (16), an upper-bound on $\lambda_{\text{max}}$ can be found as follows:

$$\tilde{\lambda}_{\text{max}} = \max_{\lambda_1} \lambda_1 e^{-\lambda_1} \frac{\Gamma(D, \nu_1)}{(D-1)!} \geq \lambda_{\text{max}}. \quad (17)$$

Note that as $N$ increases, $\tilde{\lambda}_{\text{max}}$ becomes tighter and approaches $\lambda_{\text{max}}$.

Theorem 3: For $D > 1$, there exists $N > 0$ such that

$$\tilde{\lambda}_{\text{max}} < B_{D, N},$$

which guarantees stable MRB-CRA with fast retrieval (according to Theorem 1) for $\lambda \leq \lambda_{\text{max}}$ (since $\lambda_{\text{max}} < \tilde{\lambda}_{\text{max}}$).

Proof: See Appendix C.

Consequently, for a given $D$, we can find the maximum arrival rate, $\lambda_{\text{max}}$ from (16). As long as the arrival rate is lower than or equal to $\lambda_{\text{max}}$, we can also guarantee stable MRB-CRA with fast retrieval according to Theorems 1 and 3. In fact, with $\lambda \leq \lambda_{\text{max}}$ ($< \tilde{\lambda}_{\text{max}} < B_{D, N}$), we can also expect that the rate control of A3 may not be frequently used as $K_m(q)$ might stay around $\lambda_1$ which is smaller than $D$, i.e., most transmitted packets become successful packets. However, to decide $\lambda$, we first estimate $D$ based on the performance of CS based MUD for a given set of parameters (e.g., $L$, $N$, and SNR). Thus, as mentioned earlier, the estimation of $D$ is important in MRB-CRA.

B. Throughput and Delay in the Steady State

In the steady state, for a given $\lambda$ satisfying (16), we can find $\lambda_1$ by solving (14) and (15) as shown above. With $\lambda_1$, under A1 and A2, the throughput per RB can be given by

$$T_{\text{cra}} = \sum_{n=0}^{D} \frac{e^{-\lambda_1} \lambda_1^n}{n!} n \left(1 - \frac{1}{N}\right)^{n-1}$$

$$= \lambda_1 e^{-\lambda_1} \sum_{n=0}^{D} \frac{1}{n!} \left(\lambda_1 \left(1 - \frac{1}{N}\right)\right)^n$$

$$\leq \lambda_1 e^{-\lambda_1}, \quad (19)$$

where the upper-bound becomes tight when $D - \lambda_1$ is large. Recall that $\eta = N/L$. Then, it follows

$$T_{\text{cra}} \leq \lambda_1 e^{-\lambda_1} = \lambda_1 e^{-\lambda_1/\eta}. \quad (20)$$

where $A_1 = M \lambda_1$.

We can find the average access delay from the relationship between $\lambda_1$ and $\lambda$ as shown in Fig. 3. The average number of packets to be transmitted (in a time slot), $\lambda_1$, can be seen as the number of devices in a system, while $\lambda$ is the average number of devices (within a time slot) entering into the system. Based on Little’s law [35], the average access delay (in the number of slots) can be found as

$$\tau = \frac{\lambda_1}{\lambda}. \quad (21)$$

C. Comparison With Multichannel ALOHA

It might be interesting to compare the throughput of MRB-CRA with that of conventional multichannel ALOHA.

Suppose that there are $L$ orthogonal channels per RB in conventional multichannel ALOHA. In an RB, when there are $n$ active devices, the number of successfully transmitted packets is given by $n(1 - \frac{1}{L})^{n-1}$. Thus, the average number of successfully transmitted packets is

$$T_{\text{aloha}} = \sum_{n=0}^{\infty} \left(1 - \frac{1}{L}\right)^{n-1} \frac{\lambda_n e^{-\lambda}}{n!} = \lambda e^{-\lambda}. \quad (22)$$

According to [36], the maximum stable throughput (per RB) becomes

$$T_{\text{aloha}} \leq \bar{T}_{\text{aloha}} = Le^{-1}. \quad (23)$$

Let $\Lambda = M \lambda$, which is the total arrival rate to the system. In MRB-CRA, since $D < L$, from (16) and (18), we can have the following inequality:

$$\lambda = \frac{\Lambda}{M} < B_{D, N} < L,$$

which shows that the total arrival rate, $\Lambda$, cannot be greater than $J$, i.e.,

$$\Lambda < M L = J. \quad (24)$$

However, if $\Lambda$ is sufficiently close to $J$ so that $\Lambda_1 = J$ (note that since $\Lambda < \Lambda_1$, the inequality in (24) is valid in this case), from (20), we have

$$T_{\text{cra}} \approx \lambda_1 e^{-1/\eta} \leq Le^{-1/\eta}. \quad (25)$$

As $\eta \gg 1$, we have $e^{-1/\eta} > e^{-1}$, from which it can be claimed that the throughput of MRB-CRA can be higher than that of conventional multichannel ALOHA. For example, under the optimistic assumption that $\lambda_1$ is sufficiently close to $L$, if $\eta \geq 3.258$, we can claim that the throughput of MRB-CRA can be higher than that of multichannel ALOHA by at least a factor of 2.

It is noteworthy that in [21], it is shown that the throughput of MRB-CRA can be about two-time higher than that of multichannel ALOHA when a certain controlled access probability strategy is employed. Unfortunately, in this paper, we cannot find
Fig. 4. Evolutions of $\sum_m K_m(q)$ and $\sum_m A_m(q)$ over time slots when $(L, M) = (32, 8)$, $\eta = 10$, $\bar{K} = 2L$, and SNR = 20 dB. The curves with cross (×) marks are $\sum_m K_m(q)$ and those with circle (◦) marks are $\sum_m A_m(q)$.

the throughput of MRB-CRA with fast retrial as a closed-form expression (i.e., no closed-form expression for $\lambda$ is obtained). Thus, we can consider simulations (as shown in Fig. 2 and in the next section) for comparisons with conventional multichannel ALOHA.

VI. SIMULATION RESULTS

In this section, we present simulation results for MRB-CRA with fast retrial. For simulations, we consider $C$ whose elements are independent CSCG random variables with zero mean and variance $\frac{1}{L}$. As mentioned earlier, the S-OMP algorithm is used for CS based MUD to detect multiple signals at an AP. To see the performance, we mainly consider the average number of transmitted packets per RB, $E[K_m(q)]$, and the average number of successful packets per RB, which might be identical to $\lambda$ (wile $\lambda_1 = E[K_m(q)]$) in the steady state for stable MRB-CRA.

From (21), for short access delay, we expect that the average number of transmitted packets per RB is not too larger than that of successful packets per RB.

We consider two different approaches to decide the arrival rate per RB, $\lambda$. In the first approach, we fix $D$ for given $(L, N)$ and decide $\lambda$ to be $\lambda_{\text{max}}$ in (16). In the second approach, $\lambda$ is directly decided. In Fig. 4, we present the evolution of $\sum_m K_m(q)$ and $\sum_m A_m(q)$ over time slots when $(L, M) = (32, 8)$, $\eta = 10$, $K = 2L$, and SNR = 20 dB. In the upper figure in Fig. 4, the first approach is used to decide $\lambda$ with $D = 25$. In this case, $\lambda$ becomes 16.04. On the other hand, in the lower figure in Fig. 4, the second approach is used with $\lambda = 20$. We can see that the determination of $D$ can help decide a proper arrival rate, $\lambda$, to keep $K_m(q)$ low so that the access delay is short. On the other hand, if $\lambda$ happens to be high, it may result in large $K_m(q)$’s and unstable MRB-CRA. Note that $\lambda = 20$ corresponds to about $D = 31$ multiple signals. If we use an ideal method, it might be achievable according to (7) as $L = 32$. However, the S-OMP algorithm is a greedy algorithm that has a suboptimal performance. Thus, a more realistic value for $D$ might be considered. From Fig. 4, $D = 25$ seems a reasonable estimate of $D$ to decide $\lambda$.

Fig. 5(a) shows the number of successful packets (or successfully recovered packets) and the number of transmitted packets per RB; (b) normalized access delay.

Fig. 5. Performance of MRB-CRA with fast retrial for different values of $D$ to decide $\lambda$ when $(L, M) = (32, 8)$, $\eta = 10$, $K = 2D$, and SNR = 20 dB. (a) the number of successful packets (or successfully recovered packets) and the number of transmitted packets per RB; (b) normalized access delay.
Fig. 6. Performances of MRB-CRA and conventional ALOHA for different values of arrival rate, $\lambda$ when $(L, M) = (32, 8)$, $\eta = 10$, $K = 2L$, and SNR = 20 dB: (a) throughput (or the average number of successful packets per RB); (b) normalized access delay.

Fig. 7. Performances of MRB-CRA with different numbers of $L$ for a fixed $J$ when $J = 512$, SNR = 20 dB and $\lambda = 0.8J$: (a) the total number of successful packets and the total number of transmitted packets; (b) the total complexity.

too high or the performance of CS based MUD is overestimated, $K_m(q)$ grows and the rate control of $A3$ has to be imposed to avoid any excessive delay. In Fig. 5(b), we present the normalized access delay, which is the ratio of the number of transmitted packets to the number of successful packets as in (21), where it is shown that an overestimate of $D$ results in a relatively long access delay.

For comparison with conventional multichannel ALOHA, the throughput (i.e., the average number of successful packets per RB) is shown for different values of arrival rate, $\lambda$, in Fig. 6 when $(L, M) = (32, 8)$, $\eta = 10$, $K = 2L$, and SNR = 20 dB. For conventional multichannel ALOHA, we consider the controlled access probability proposed in [37] with the assumption that the number of transmitted packets at each slot is available at the devices to decide their access probability. We can see that MRB-CRA outperforms conventional multichannel ALOHA in terms of both the throughput and access delay.

Note that in Fig. 6, the throughput and access delay of MRB-CRA behave differently when $\lambda / L \leq 0.6$ or $\lambda \geq 19$. As mentioned earlier, if $\lambda$ is too high, the rate control of $A3$ is imposed to keep the access delay reasonable, which, however, results in a lower throughput.

In order to see the impact of $L$ on the performance, we show the total number of successful packets and the total number of transmitted packets (i.e., $\mathbb{E}[\sum_m K_m(q)]$) as well as the complexity for different values of $L$ when the total number of subcarriers is fixed as $J = 512$ in Fig. 7 with SNR = 20 dB and $\lambda = 0.8J$ (or $\lambda = 0.8L$). As mentioned earlier, the performance of S-OMP is improved as $L$ increases, which means that $D$ can increase with $L$ (which can be confirmed by Fig. 2). Thus, for given $\lambda = 0.8L$, $D$ should be at least greater than $0.8L$ for reasonable performances of MRB-CRA or stable MRB-CRA (with reasonably short access delay). As shown in Fig. 7(a), we need $L \geq 32$ for reasonably good performances. Furthermore, as $L$ increases, we can see that the performance is improved as expected. However, Fig. 7(b) shows that the complexity increases with $L$ (as $M$ decreases with $L$ since $J$ is fixed). Thus, one big RB is not desirable for CRA due to high computational complexity. As mentioned earlier, this exhibits the trade-off between the performance and complexity.

Fig. 8, we show the number of successful packets and the number of transmitted packets for different values of the virtual bandwidth expansion factor, $\eta$, when $(L, M) = (32, 8)$, $D = 25$, and SNR = 20 dB. It is shown that as $\eta$ increases, the number of transmitted packets per RB, $\mathbb{E}[K_m(q)]$, decreases. Thus, it is desirable to have a large $\eta$ (i.e., greater than 5) to generate more virtual channels per RB to reduce the probability of collision and result in a better performance. However, since
When \( R_k \) increases, the increase of \( \eta \) results in a higher computational complexity. Thus, \( \eta \) should not be too large. From Fig. 8, \( \eta = 6 \) or 7 seems a reasonable choice to provide a good performance with a relatively low complexity.

VII. CONCLUDING REMARKS

We have proposed an MRB-CRA scheme with fast retrial in this paper. It was shown that the proposed scheme is not only scalable, but also computationally efficient in terms of receiver’s complexity due to multiple RBs. We carried out the stability analysis based on the Foster-Lyapunov stability criterion, and derived a maximum arrival rate for stable MRB-CRA with fast retrial. Furthermore, we studied a steady state analysis to find the throughput and delay of MRB-CRA. Through analysis and simulation results, it was shown that the proposed MRB-CRA scheme can have a higher throughput than conventional multi-channel ALOHA with a lower access delay and enjoy a trade-off between the performance and complexity in terms of the number of RBs.

APPENDIX A

PROOF OF THEOREM 1

To show that \( k(q) \) is positive recurrent, we can use the notion of Lyapunov function that is a nonnegative function [35]. In particular, from a Lyapunov function, we can have the drift function, which represent the variation of Lyapunov function in time. If the drift function satisfies certain conditions, we can show that \( k(q) \) is positive recurrent.

Let \( V(q) = \sum_{m=1}^{M} K_m(q) \) be the Lyapunov function, which is a nonnegative function for

\[
\Omega = \{ k = [K_1 \ldots K_M]^T \mid K_m \in \{0, \ldots, MK\} \}.
\]

Note that \( \Omega \) is a finite set as the maximum value of \( K_m(q) \) is \( MK \) due to the assumption of A3. Based on Foster’s theorem [35], using the Lyapunov function \( V(q) \), we can show that \( k(q) \) is positive recurrent if (13) holds.

In (11), since the next RB is uniformly chosen at random by an active device experiencing collision, it can be shown that

\[
\mathbb{E}[R_{m,i}([K_i(q)]_D) \mid [K_i(q)]_D = i] = \frac{i}{M}.
\]

Suppose that \( K_m \leq D \). Then, \([K_m]_D \) can be expressed as

\[
[K_m]_D = K_m - \sum_{n=1}^{N} \mathbb{I}(X_n^{K_n} = 1),
\]

where \( X_n^{K_n} \) denotes the number of active devices that choose SC \( n \) when there are \( K_n \) active devices in RB \( m \). From (26) and (27), we have

\[
\mathbb{E}[R_{m,i}([K_i(q)]_D) \mid K_i(q) = K_i] = \frac{K_i - \sum_{n=1}^{N} \mathbb{E}(X_n^{K_n})}{M} \mathbb{I}(K_i = 1).
\]

Since the event of \( X_n^{K_n} = 1 \) means that there is only one device choosing SC \( n \) and the other devices choosing the other SCs when there are \( K_i \) active devices in RB \( l \), it can be shown that

\[
\mathbb{P}(X_n^{K_i} = 1) = \frac{K_i}{N} \left( 1 - \frac{1}{N} \right)^{K_i-1}.
\]

Substituting (29) into (28), and from (13), it can be shown that

\[
\mathbb{E}[K_i(q+1) \mid k(q)] = \mathbb{E} \left[ \sum_{l=1}^{M} R_{m,i}([K_i(q)]_D) + \bar{A}_m (q+1) \mid k(q) \right] = \frac{1}{M} \sum_{l=1}^{M} U_D(K_i(q)) + \bar{A}_m \mathbb{I}(K_m(q) \leq \bar{K}),
\]

where

\[
U_D(K_i) = \begin{cases} K_i, & \text{if } K_i > D; \\ K_i \left( 1 - \frac{1}{N} \right)^{K_i-1}, & \text{o.w.} \end{cases}
\]

Let \( \mathcal{C} = \{ k \mid K_m < B_{D,N} \text{ or } D \leq K_m \leq MK, \ m = 1, \ldots, M \} \). Suppose that \( k(q) \in \Omega - \mathcal{C} \). In this case, we have

\[
U_D(K_i(q)) = K_i(q) \left( 1 - \left( 1 - \frac{1}{N} \right)^{K_i(q)-1} \right),
\]

\[
\bar{A}_m \mathbb{I}(K_m(q) \leq \bar{K}) = \bar{A}_m,
\]

the drift of \( V(q) \) can be found as

\[
\mathbb{E}[V(q+1) \mid k(q)] - V(q) = \frac{1}{M} \sum_{m=1}^{M} U_D(K_m(q)) - K_m(q) + \bar{A}_m
\]

\[
= \sum_{m=1}^{M} \bar{A}_m - K_m(q) \left( 1 - \frac{1}{N} \right)^{K_m(q)-1}.
\]
Consider the function of $k$, $q(k) = k(1 - \frac{1}{N})^{k-1}$, which is an increasing function of $k$ when $0 \leq k \leq -\frac{1}{\ln(1 - \frac{1}{N})} < N$. From this and noting that $D \leq N$, we have

$$K_m(q) \left(1 - \frac{1}{N}\right)^{K_m(q)-1} \leq D \left(1 - \frac{1}{N}\right)^{D-1} = B_{D,N},$$

which implies that

$$\mathbb{E}[V(q+1) \mid k(q)] - V(q) \leq \sum_{m=1}^{M} (\bar{A}_m - B_{D,N}). \tag{33}$$

From (33), if (13) holds, we can conclude that

$$\mathbb{E}[V(q+1) \mid k(q)] - V(q) < 0, \text{ if } k(q) \in \Omega - C. \tag{34}$$

On the other hand, if $k(q) \in C$, we have either $U_D(K_i(q)) - K_i(q) + \bar{A}_m \leq \bar{K}$ or $U_D(K_i(q)) - K_i(q) + \bar{A}_m \leq \bar{A}_m$ (when $K_i(q) > D$) or $U_D(K_i(q)) - K_i(q) + \bar{A}_m \geq \bar{A}_m$ (when $K_i(q) < B_{D,N}$). Thus, we have

$$\mathbb{E}[V(q+1) \mid k(q)] - V(q) \leq \sum_{m=1}^{M} \bar{A}_m, \text{ if } k(q) \in C. \tag{35}$$

From (34) and (35), we can see that $k(q)$ is positive recurrent under the Foster-Lyapunov stability criterion [35].

**APPENDIX B**

**Proof of Theorem 2**

Under A1 and A2, from (8), it can be shown that

$$\mathbb{E} \left[ [K_m(q)_{D}] \right] = D \sum_{n=0}^{D} \left( n - n \left(1 - \frac{1}{N}\right)^{n-1} \right) p_n + \sum_{n=D+1}^{\infty} n p_n,$$

where $p_n = \text{Pr}(K_m(q) = n)$. Since $K_m(q) \sim \text{Pois}(\lambda_1)$, we have

$$\mathbb{E} \left[ [K_m(q)_{D}] \right] = \lambda_1 - \lambda_1 \sum_{n=0}^{D-1} n \left(1 - \frac{1}{N}\right)^n \frac{\lambda_1^n e^{-\lambda_1}}{n!}$$

$$= \lambda_1 \left(1 - e^{-\frac{1}{N}} \frac{\Gamma(D, \nu_1)}{(D-1)!}\right), \tag{36}$$

which completes the proof.

**APPENDIX C**

**Proof of Theorem 3**

For convenience, let $\bar{\lambda}_1$ represent the solution to (17). In [21], it is shown that $\bar{\lambda}_1$ is smaller than $D$ for $D > 1$, i.e., $\bar{\lambda}_1 < D$. We can also show that

$$\bar{\lambda}_{\max} < \bar{\lambda}_1 < D, \text{ for } D > 1. \tag{37}$$

The first inequality in (37) is obtained by the fact that

$$\bar{\lambda}_1 e^{-\bar{\lambda}_1(1 - 1/N)} \sum_{n=0}^{D-1} \frac{(\bar{\lambda}_1(1 - 1/N))^n}{n!} < \bar{\lambda}_1$$

from (17). Thus, there exists $\epsilon > 0$, which is independent of $N$, such that $\bar{\lambda}_{\max} = D - \epsilon$. For given $D$, there exists a $N_\epsilon$ such that the following holds for $N \geq N_\epsilon$:

$$B_{D,N} - \bar{\lambda}_{\max} = D \left(1 - \frac{1}{N}\right)^{D-1} - D + \epsilon$$

$$\geq D \left(1 - \frac{D - 1}{N} - 1 + \frac{\epsilon}{D}\right)$$

$$= D \left(\frac{\epsilon}{D} - \frac{D - 1}{N}\right) > 0,$$

which completes the proof.

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