Random Access With Layered Preambles Based on NOMA for Two Different Types of Devices in MTC

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Abstract—In machine-type communication (MTC), random access has been employed for a number of devices and sensors to access uplink channels using a pool of preambles. To support different priorities due to various quality-of-service (QoS) requirements, random access can be generalized with multiple pools, which may result in low spectral efficiency. In this paper, for high spectral efficiency, random access with layered preambles (RALP) is proposed to support devices with two different priorities based on the notion of power-domain non-orthogonal multiple access (NOMA). In RALP, two groups of devices, namely type-1 and type-2 devices, are supported with different priorities, where type-1 devices have higher priority than type-2 devices. Closed-form expressions are derived for the detection performance of preambles transmitted by type-1 devices, which can be used for a certain performance guarantee of type-1 devices of high priority. Low-complexity preamble detection methods are also discussed.

Index Terms—Machine-type communication, random access, preambles, power-domain NOMA.

I. INTRODUCTION

T

HE Internet of Things (IoT) is a network of things that are connected for a number of applications including smart cities and factories [1], [2]. To support the connectivity, a number of different approaches have been proposed [3]. For example, in [4], low-power wide area networks (LPWAN) are studied to support devices with long range communications in unlicensed bands. Cellular IoT using machine-type communication (MTC) [5], [6] is also considered to support the connectivity of IoT devices and sensors in cellular systems [7]. In [8], a deployment study of narrowband IoT (NB-IoT) [6] is presented for IoT applications with sensors and devices deployed over a large area within a cellular system.

Due to sparse activity and sporadic traffic of devices and sensors in MTC [9], random access is used to keep signaling overhead low, and various random access schemes with a set of preambles are studied in handshaking process to establish connections [5], [6], [10], [11].

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To support a large number of devices with limited bandwidth, non-orthogonal preambles can be used and the detection of non-orthogonal preambles can be carried out using multiuser detection approaches [12], [13]. Since a fraction of devices are active at a time, the sparse user activity can be taken into account to design multiuser detectors [14]–[16]. The sparse user activity can be represented by a sparse vector so that the resulting random access can be seen as a sparse signal recovery problem in the context of compressive sensing (CS) [17], which is called compressive random access [18], [19]. Compressive random access can be used for grant-free random access [20], [21] and be combined with massive multiple-input multiple-output (MIMO) [22]–[25].

Most compressive random access schemes use a pool of preambles and any device that has data to transmit is to randomly choose one preamble from the pool and transmit it. Although preamble collisions (when multiple devices choose the same preamble) happen, this is a way to support a large number of devices with a limited number of preambles (due to limited bandwidth), while it is also possible to assign unique sequences to devices [26]. Since there is only one pool, each device may have almost equal chance to be connected. For example, each active device has the same probability of preamble collision. As a result, no priority is introduced in conventional compressive random access. However, as in [9], [27]–[29], devices can have different priorities depending on their Quality-of-Service (QoS) requirements.

To support different priorities, in this paper, we consider random access with layered preambles (RALP) based on the notion of power-domain non-orthogonal multiple access (NOMA) [30], [31]. In particular, the main contributions are it is assumed that there are two different types of devices in terms of priority, namely type-1 and type-2 devices, where type-1 devices have higher priority than type-2 devices, while the number of active type-1 devices is much fewer than that of active type-2 devices. In RALP, it is aimed that the probability of detection errors of type-1 devices is to be sufficiently low, while that of type-2 devices is arbitrary. In summary, the main contributions of the paper are as follows: i) using layered preambles based on power-domain NOMA, a random access scheme to support two different types of devices is proposed; ii) a low-complexity preamble detection approach is derived using successive interference cancellation (SIC) and a well-known machine learning algorithm, i.e., a variational inference.
There are a number of related works. For example, in [21], layered preambles are also considered using the notion of power-domain NOMA, while different priorities are not taken into account. In terms of supporting two different priorities in MTC, [28] is the most related work, which mainly focuses on dynamic resource allocation and user barring without using layered preambles. In fact, since RALP in this paper can provide different priorities with layered preambles and different detection performance, it can be used within dynamic resource allocation and user barring schemes, which can be seen as a further work.

Note that there are also other NOMA-based random access approaches where each device has a unique sequence (as a result, they do not need to use a shared pool of preambles as in MTC). For example, in [21] and [32], non-orthogonal Gaussian and low-density signatures, respectively, are used to improve the spectral efficiency in random access and joint channel estimation and detection is considered. In [33], as in [32], non-orthogonal Gaussian and low-density signatures are used for unique devices’ signature in random access, where a Bayesian receiver is designed.

The rest of the paper is organized as follows. In Section II, the system model is presented. In Section III, RALP is introduced using the notion of power-domain NOMA to support two different types of devices with single resource block. In Sections IV and V, the detection methods are studied for RALP with performance analysis for devices of high priority. Simulation results are presented in Section VI. Finally, we conclude the paper with remarks in Section VII.

Notation: Matrices and vectors are denoted by upper- and lower-case boldface letters, respectively. The superscripts $\text{H}$ and $\text{T}$ denote the transpose and complex conjugate, respectively. The $p$-norm of a vector $a$ is denoted by $\|a\|_p$ (if $p = 2$, the norm is denoted by $\|a\|$ without the subscript). $\mathbb{E}[\cdot]$ and $\text{Var}(\cdot)$ denote the statistical expectation and variance, respectively. $\mathcal{CN}(a, R)$ represents the distribution of circularly symmetric complex Gaussian (CSG) random vectors with mean vector $a$ and covariance matrix $R$. The Q-function is given by $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$.

II. SYSTEM MODEL

In this section, the system model is presented with two different types of devices.

A. Random Access for MTC

Consider a system that consists of a BS and a large number of devices that are synchronized for MTC. Suppose that a fraction of devices are active at a time and use random access to establish connections to transmit their data (e.g., random access channel (RACH) procedure in the long-term evolution advanced (LTE-A) systems [5]). For random access, we assume that a common pool of preambles is used [5], [6]. A device that has data packets to transmit, which is called an active device, randomly chooses a preamble from the pool and transmits it to the BS (through physical random access channel (PRACH) in RACH procedure) which is the first step of a handshaking process to establish connection in most MTC schemes (e.g., [5]). Due to multiple active devices that choose the same preamble, there exist preamble collisions and this step can be seen as contention-based access. There are few more steps in the handshaking process to finally allocate dedicated uplink (data) channels (which are physical uplink shared channel (PUSCH) in RACH procedure) to active devices so that they can transmit their data packets to the BS.

Note that it is possible that each device can have a unique preamble as a signature sequence so that the BS can identify different devices with their unique preambles. However, since the number of devices can be too large to have unique preambles, devices can share a common pool of preambles provided that devices’ activity is sparse (i.e., only a fraction of devices are active at a time) at the cost of preamble collisions.

B. Different Types of Devices

For the simplicity, we only consider two different types of devices in this paper, which are referred to as type-1 and type-2 devices, as follows:

- **Type-1 devices**: They require a short access delay, while the number of them is much fewer than that of type-2 devices.
- **Type-2 devices**: They do not require any constraint on access delay.

According to [28], type-1 and type-2 devices can be seen as delay-sensitive and delay-tolerant devices, respectively.

In order to support two different types of devices, two different (orthogonal) radio resource blocks (RBs) can be allocated. For each type of devices, a pool of preambles can be associated with an RB. This is the case to build two different access systems. Note that, with one RB, a pool of preambles can be dynamically divided into two sub-pools of preambles to support two types of devices with different probabilities of preamble collisions as in [28]. In this case, in order to have a sufficiently large number of preambles, a wide system bandwidth might be required, which may result in a low spectral efficiency.

In fact, the access delay depends on not only preamble collisions, but also preamble detection errors, since an active device may re-transmit another preamble if the preamble transmitted previously is not detected (due to either collision or detection error). Thus, for a short access delay, both the probabilities of preamble collisions and detection errors have to be low. This implies that it is also necessary to take into account the probability of preamble detection errors to support different priorities, which is not considered in [28].

In this paper, based on the notion of power-domain NOMA, we design layered preambles with one RB to support different priorities between type-1 and type-2 devices with a high spectral efficiency in terms of the probability of preamble detection errors, which will be discussed in Section III.

There can be detection errors due to channel fading and/or the noise at the BS.
III. POWER-DOMAIN NOMA FOR LAYERED PREAMBLES WITH SINGLE RB

In this section, we propose layered preambles to support two different types of devices with one RB based on the notion of power-domain NOMA.

A. Alltop Sequences for Layered Preambles

For different priorities, it is necessary to ensure type-1 devices have a better performance of preamble detection than type-2 devices, which leads to a short access delay. To this end, while there can be a number of different ways, we apply power-domain NOMA to certain sequences of good cross-correlations for preambles.

Suppose that an RB is allocated to support two different types of devices. Let $N$ be the length of preamble sequences for a given RB. Since the system bandwidth is proportional to $N$, as long as $N$ is fixed, the system bandwidth is fixed. If all the preambles are orthogonal, the total number of preambles, denoted by $L$, is equal to $N$. However, if non-orthogonal preambles are allowed, $L$ can be larger than $N$. In particular, we consider Alltop sequences for non-orthogonal preambles as an example, while different sequences can also be used (e.g., Zadoff-Chu sequences [34]). With Alltop sequences, we have $L = N^2$ for a prime $N \geq 5$ [35].

Let $x_l$ denote the $l$th preamble sequence of length $N$ with $||x_l|| = 1$ for all $l$. Denote by $L_1$ the number of preamble sequences assigned to type-$1$ devices. Let $L_1 = \{x_1, \ldots, x_N\}$ be the set of preambles for type-1 devices with $L_1 = N$. In addition, let $L_2 = \{x_{N+1}, \ldots, x_{N+L_2}\}$ denote the set of preambles for type-2 devices with $L_2 \leq N(N-1)$. For convenience, the $l$th preambles of $L_1$ and $L_2$ are denoted by $c_l$ and $c_{l_N}$, respectively. Throughout the paper, we assume that $L_1$ is a set of orthogonal preambles. On the other hand, $L_2$ is a set of non-orthogonal preambles. Since Alltop sequences are used, the correlation between any two non-orthogonal preambles is $1/N$. Thus, the correlation between any two different preambles in $L_2$ is $1/N$, while that in $L_1$ is 0. The reason why orthogonal sequences are used for $L_1$ will be explained later. In addition, the correlation between one in $L_1$ and another one in $L_2$ is $1/N$. It is noteworthy that although $L_2$ can be as large as $N(N-1)$ and a large $L_2$ can lower the preamble collision for type-2 devices, a large $L_2$ may not be desirable in terms of the complexity and performance of the preamble detection at the BS (this issue will be discussed in detail in Sections V and VI).

B. Power-Domain NOMA

Denote by $h_{k1}$ and $h_{k2}$ the channel vector of the $k$th active device of type-1 and type-2, respectively. Let $M$ denote the number of antennas at the BS. Thus, $h_{k1}, h_{k2} \in \mathbb{C}^{M \times 1}$. For power-domain NOMA with two different pools of preambles, we consider the following assumption based on [36].

A1) Let $P_{1x,k}$ and $P_{2x,k}$ denote the transmit powers of the $k$th active type-1 and type-2 devices, respectively. Then, $P_{1x,k}$ and $P_{2x,k}$ are decided to be inversely proportional to the distance between the BS and the active devices to compensate path loss via power control so that

$$
\begin{align*}
\sqrt{P_1} h_{k1} \sqrt{P_{1x,k}} &= v_k \sqrt{P_x}, \\
\sqrt{P_2} h_{k2} \sqrt{P_{2x,k}} &= v_k \sqrt{P_x},
\end{align*}
$$

where $P_x$ represents the (average) receive power for type-$i$ devices, $i \in \{1, 2\}$ and $v_k \sim \mathcal{CN}(0, I)$ are independent for all $k$ (i.e., Rayleigh fading is assumed for small-scale fading).

To ensure different priorities, we assume that $P_1 > P_2$. Thus, as shown in Fig. 1, the preambles for type-1 devices (i.e., $L_1$) are not only orthogonal, but also transmitted with a higher power than those for type-2 devices (i.e., $L_2$). As a result, type-1 devices’ preambles can be more reliably detected than type-2 devices’ preambles without any interference between active type-1 devices of high receive power, $P_1$. For convenience, the resulting approach to random access with priority is referred to as RALP. The preamble detection for RALP will be studied in Sections IV and V.

Denote by $K_{i,l}$ the index set of the active type-$i$ devices that choose preamble $l$ in $L_i$. Thus, the index set of all active type-$i$ devices, denoted by $K_i$, becomes $K_i = \bigcup_l K_{i,l}$. Let $K_i$ be the number of active type-$i$ devices, i.e., $K_i = |K_i|$. Note that since each active device chooses only one preamble, $K_i = \sum_l |K_{i,l}|$, where $K_{i,l} = |K_{i,l}|$. Let

$$
\begin{align*}
\mathbf{s}_l &= \sum_{k \in K_{i,l}} v_k, \quad l = 1, \ldots, L_1, \\
\mathbf{s}_l &= \sum_{k \in K_{i,l}} v_k, \quad l = 1, \ldots, L_2,
\end{align*}
$$

to represent the superposition of the channel vectors associated with the active devices that choose the same preamble. Then, the received signal at the BS is given by

$$
\mathbf{Y} = \sum_{l=1}^{L_1} \sqrt{P_1} \mathbf{s}_l c_l^H + \sum_{l=1}^{L_2} \sqrt{P_2} \mathbf{s}_l c_l^H + \mathbf{N} \in \mathbb{C}^{M \times N},
$$

where $[\mathbf{N}]_{m,n} \sim \mathcal{CN}(0, \sigma^2)$ represents the background noise. In (3), the $m$th row of $\mathbf{Y}$ represents the received signal at the $m$th antenna when active devices transmit randomly selected preambles.

As shown in (3), since $P_1 > P_2$, the received signals from active type-1 devices are stronger than those from active type-2 devices. As a result, the BS may need to detect the preambles transmitted from active type-1 devices first. Once they are detected, they can be removed (or suppressed) for
the detection of the preambles transmitted from active type-2 devices. We discuss low-complexity detection approaches in Sections IV and V.

IV. DETECTION OF PREAMSLES TRANSMITTED BY TYPE-1 DEVICES

In general, for the detection of transmitted preambles, which is also called the user activity detection [14], [15], there are optimal approaches based on joint detection. In this case, the complexity is proportional to $2^{L_1} \times 2^{L_2} = 2^{L_1+L_2}$, which is prohibitively high. As a result, we may resort to low-complexity suboptimal detection approaches. To this end, we consider a two-step approach for RALP. In the first step, the detection of preambles transmitted by type-1 devices, which is referred to as the type-1 preamble detection, is carried out by taking advantage of the orthogonality of their preambles (i.e., $L_1$) and $P_1 > P_2$. In the second step, all the preambles transmitted by type-1 devices are removed and the detection of the preambles transmitted by type-2 devices (which is also referred to as the type-2 preamble detection) is carried out. In this section, we focus on the first step and analyze the performance of preamble detection in terms of $P_1$ and $P_2$.

A. Correlator Detector

Taking advantage of the orthogonality of $L_1$ (i.e., the preambles for type-1 devices), the BS can detect them using the following correlator’ output:

$$g_l = Yc_l = \sqrt{P_1}s_l + \sqrt{P_2}\sum_{t=1}^{L_2} s_t\bar{c}_t^l c_l + n_l, \quad l = 1, \ldots, L_1, \quad (4)$$

where $n_l = Nc_l$. Clearly, due to the orthogonality of $L_1$, there is no interference from the other active type-1 devices of high receive power.

Letting $\bar{c}_t^l c_l = \rho_{l,t}$, the $m$th element of $g_l$ corresponding to the $m$th antenna is given by

$$g_{m,l} = \sqrt{P_1}s_{m,l} + \sum_{t=1}^{L_2} \rho_{l,t}\sqrt{P_2}s_{m,t} + n_{m,l}, \quad (5)$$

where $g_{m,l}$, $s_{m,l}$, $s_{m,t}$, and $n_{m,l}$ are the $m$th elements of $g_l$, $s_l$, $s_t$, and $n_l$, respectively. Then, according to the assumption of A1), since each element of channel vectors is independent CSCG and $|\rho_{l,t}| = \frac{K}{\sqrt{N}}$, it can be seen that

$$\sum_{t=1}^{L_2} \rho_{l,t}\sqrt{P_2}s_{m,t} + n_{m,l} \sim CN(0, I_2), \quad (6)$$

where $I_2 = \frac{K}{N}P_s + N_0$. As a result, the detection of $c_l$ in $Y$ can be carried out with the correlator’s output, $g_l$ in (4), which can be seen as Gaussian signal detection in the presence of Gaussian noise that is in (6).

B. Hypothesis Testing and Performance Analysis

For two hypotheses, letting $H_0$ and $H_1$ denote the cases of $K_{l,t} = 0$ (i.e., there is no type-1 device that chooses $c_l$) and $K_{l,t} = 1$ (i.e., there is only one type-1 device that chooses $c_l$), respectively, we have

$H_0$: $g_{m,l} \sim CN(0, I_2)$ versus $H_1$: $g_{m,l} \sim CN(0, P_1 + I_2)$

which is Gaussian signal detection as mentioned earlier. In addition, since $|g_{m,l}|^2$ follows an exponential distribution, the test statistic, $Z = ||g||^2$, follows a Gamma distribution and the following hypothesis testing including the hypothesis that there are multiple active type-1 devices choosing $c_l$, denoted by $H_c$, can be formulated:

$H_0$: $Z \sim f_0(z) = \text{Gamma}(M, I_2)$

$H_1$: $Z \sim f_1(z) = \text{Gamma}(M, P_1 + I_2)$

$H_c$: $Z \sim f_c(z) = \text{Gamma}(M, K_{l,t}P_1 + I_2), K_{l,t} \geq 2, \quad (7)$

where $\text{Gamma}(n, \theta) = \frac{x^{n-1}e^{-x}}{\theta^n n!}$, for $x \geq 0$ with $n, \theta > 0$, is the Gamma distribution and $\Gamma(n)$ is the Gamma function.

According to (7), there can be two decision threshold values, $\tau_1$ and $\tau_2$, and decision can be carried out as follows:

$$Z \leq \tau_1: \text{Accept } H_0$$

$$\tau_1 < Z \leq \tau_2: \text{Accept } H_1$$

$$Z > \tau_2: \text{Accept } H_c. \quad (8)$$

Furthermore, it is also possible to determine parameters (e.g., $P_1$ and $\tau_1$) for a certain target performance. Denote by $P_{d,\ell}$ the error probability when $H_d, d \in \{0, 1, c\}$, accepted, when $H_\ell$ is true. The probabilities of missed detection (MD) and false alarm (FA) are given by

$$P_{0,\text{MD}} = P_{0|1} = \int_0^{\tau_1} f_1(z) \, dz$$

$$P_{c,\text{MD}} = P_{c|1} = \int_{\tau_1}^{\tau_2} f_1(z) \, dz$$

$$P_{1,\text{MD}} = P_{1|c} = \int_{\tau_1}^{\tau_2} f_c(z) \, dz$$

$$P_{\text{FA}} = P_{1|0} + P_{c|0} = \int_{\tau_1}^{\infty} f_0(z) \, dz. \quad (9)$$

Using the Gamma distributions in (7), all the error probabilities in (9) can be found as closed-form expressions. We have a few remarks on the error events.

- There are three events of MD associated with the first three probabilities in (9). The events of MD when $H_1$ is true may lead to re-transmissions by the related active type-1 devices, while the event of MD when $H_c$ is true has to be rectified by further steps in the handshaking process. In addition, with layered preambles, the event of MD associated with $P_{0|1}$ leads to error propagation and high interference that degrades the performance of preamble detection of type-2 devices, while that with $P_{c|1}$ leads to the signal dimension reduction has less serious impact on the performance as will be discussed in Section V.
In general, an event of FA results in incorrect acknowledgment of successful preamble transmission to an inactive device in the handshaking process, which is disregarded by the inactive device. Thus, it might be tolerable to have a relatively high probability of FA. However, with the proposed layered preambles, any FA events can lead to error propagation through SIC and a degraded performance of type-2 preamble detection. However, the resulting performance degradation is not serious as that due to the event of MD associated with \( P_{01} \), which will be explained in Section V.

A salient feature of the proposed approach, i.e., RALP, is that it can have guaranteed performance for type-1 devices, because the error probabilities can be found with given parameters as shown in (9) (thanks to the simple detection approach (i.e., the correlator detector) whose performance can be simply obtained as closed-form expressions\(^2\) in (9)).

### C. Key Error Probabilities

In this subsection, we study key error probabilities of the type-1 preamble detection.

Provided that \( K_1 \ll L_1 = N \) and \( P_1 \) is sufficiently high, it is expected that the events of MD associated with \( P_{01} \) and \( P_{1|c} \) in (9) may not frequently happen. Thus, we may focus on the first two probabilities of errors, i.e., \( P_{FA} \) and \( P_{MD} = P_{01} \), in (9), which is mainly decided by \( \tau_1 \). With a small \( \epsilon > 0 \), \( \tau_1 \) can be decided to keep

\[
P_{MD} \leq \epsilon
\]

(10)
to not only minimize the impact of error propagation and high interference on the performance of type-2 preamble detection, but also reduce the number of re-transmissions for low access delay.

Note that although \( \epsilon \to 0 \), there are active type-1 devices that fail to transmit their preambles because of preamble collisions. Thus, with a sufficiently low \( \epsilon \), re-transmissions are mainly caused by preamble collisions for type-1 devices. As a result, for a low access delay, the probability of preamble collision has to be controlled by limiting the number of type-1 devices per RB such that \( E[K_1] \ll N \). This issue is related user barring [28], which is beyond the scope of the paper.

From (7), (10) can be rewritten as

\[
P_{MD} = F_1(\tau_1) = e^{-\nu_1} \sum_{m=M}^{\infty} \frac{\nu_1^m}{m!} \leq \epsilon,
\]

(11)
where \( F_1(\cdot) \) represents the cdf of \( f_1(\cdot) \) and \( \nu_1 = \frac{\tau_1 K_1}{P_1 + \nu_1} \). Clearly, \( F_1(\tau_1) \) corresponds to the probability that a Poisson random variable with mean \( \nu_1 \) is greater than or equal to \( M \). Thus, for a low \( P_{MD} \), \( \nu_1 < M \) is required.

Fig. 2 shows the value of \( \nu_1 \) as a function of \( M \) for a given \( \epsilon \in \{10^{-2}, 10^{-3}\} \). Denote by \( \nu_1(M, \epsilon) \) the value of \( \nu_1 \) that satisfies the quality in (11) for given \( \epsilon \) and \( M \). Consequently, we can have the following relationship:

\[
\nu_1(M, \epsilon) = \frac{\tau_1}{P_1 + \frac{K_1 P_{FA}}{N} + N_0},
\]

(12)
\(^2\)On the other hand, the performance of type-2 preamble detection is not easily obtained as closed-form expressions.

which can be used to decide \( \tau_1 \) for given \( P_1, K_2, \) and \( P_2 \). According to [37], we have

\[
\lim_{\epsilon \to 0} \lim_{M \to \infty} \frac{1}{M} \ln P_{FA} = -D(\tilde{f}_1 || f_0),
\]

(13)

where \( D(\tilde{f}_1 || f_0) = \mathbb{E}_0[\ln \frac{\tilde{f}_1(z)}{f_0(z)}] \) is the Kullback Leibler (KL) divergence or distance when \( M = 1 \). Here, \( \tilde{f}_1(z) \) represents \( f_i(z) \), \( i = 0, 1 \), with \( M = 1 \) and \( \mathbb{E}_0[\cdot] \) represents the expectation with respect to \( f_0(z) \). From (7), it can be shown that

\[
D(\tilde{f}_1 || f_0) = \frac{P_1}{T_2} - \ln \left( 1 + \frac{P_1}{T_2} \right) \geq 0.
\]

(14)
Consequently, with \( P_{MD} = P_{01} \leq \epsilon \), we can see that \( P_{FA} \) decreases exponentially with \( M \) (i.e., a large \( M \) can result in a low \( P_{FA} \)). In Fig. 3, the KL distance in (14) is shown as a function of \( P_1/T_2 \).
V. Detection of Preambles Transmitted by Type-2 Devices

In this section, we discuss the type-2 preamble detection based on the notion of sparse signal recovery under the assumption that $K_2 \ll L_2$.

A. SIC and Error Propagation

Provided that the type-1 preamble detection is successfully carried out, the type-2 preamble detection can be considered with SIC. For convenience, let $\mathcal{J}_i$ denote the index set of the preambles that are chosen by active type-i devices, i.e.,

$$\mathcal{J}_i = \{ l : \kappa_{i,l} \geq 1 \}.$$ 

For $l \in \mathcal{J}_1$, we assume that $\frac{1}{\sqrt{P}} s_{i,l}$ is an estimate of $s_l$. Thus, for SIC, the received signal from active type-1 devices can be reconstructed and removed as follows:

$$\bar{Y} = Y - \sum_{l \in \mathcal{J}_1} g_l c_l^H = Y P_1$$

$$= \left( \sum_{l=1}^{L_2} \sqrt{P_2} s_{l} c_l^H + N \right) P_1,$$ 

(15)

where $P_1 = I - \sum_{l \in \mathcal{J}_1} c_l c_l^H$ is an orthogonal projection matrix. This implies that SIC results in the signal suppression that suppresses all the signals in the subspace spanned by $c_l$, $l \in \mathcal{J}_1$.

From (15), we can see the impact of error propagation on the performance of type-2 preamble detection. For the event of FA, suppose that $c_1$ is incorrectly detected as a transmitted one. In this case, the orthogonal projection matrix becomes

$$P_1 = I - \sum_{l \in \mathcal{J}_1} c_l c_l^H - c_1 c_1^H.$$ 

(16)

This results in unnecessary signal suppression associated with the subspace spanned by $c_1$, which leads to the dimension reduction.

For the event of MD, suppose that $c_1$ belongs to $\mathcal{J}_1$ (i.e., it is a transmitted preamble), but it is not detected. Then, $P_1$ is modified as $P_1 = I - \sum_{l \in \mathcal{J}_1} c_l c_l^H + c_1 c_1^H$, which leads to

$$\bar{Y} = \sqrt{P_2} s_1 c_1^H + \left( \sum_{l=1}^{L_2} \sqrt{P_2} s_{l} c_l^H + N \right) P_1.$$ 

(17)

Clearly, the type-2 preamble detection suffers from the strong interference due to undetected and unsuppressed preambles of type-1 devices. Compared to the dimension reduction due to FA, the presence of strong interference due to MD may result in a severe performance degradation, which will be demonstrated in Section VI.

B. Preamble Detection as Sparse Vector Estimation

In this subsection, we consider the type-2 preamble detection after SIC as a sparse vector estimation problem. For simplicity, it is assumed that there are no FA and MD errors when detecting preambles from type-1 devices.

Let $C_u$ be the matrix consisting of the column vectors that are $c_l$, $l \notin \mathcal{J}_1$. Clearly, $C_u$ is orthogonal to $c_l$, $l \in \mathcal{J}_1$ and $P_1 C_u = C_u$. Denote by $\check{s}_m^H$ the $m$th row of $\check{Y}$ and let $z_m = (\check{s}_m^H C_u)^H = C_u^H \check{s}_m$ and $C = [\check{c}_1 \ldots \check{c}_{L_2}]$. Then, after some manipulations, it can be shown that

$$z_m = C_u^H C a_m + u_m, \quad m = 1, \ldots, M,$$ 

(18)

where $u_m$ is the $m$th row of $NP_1 C_u$, $u_m \sim CN(0, N_0 I)$, and

$$|a_m|_0 \leq K_2 \quad \text{and} \quad \text{supp}(a_m) = \text{supp}(a_{m'})$$,

$m, m' = 1, \ldots, M$. 

(20)

In addition, letting $J_1 = |\mathcal{J}_1|$, $\Phi$ becomes a $J_1 \times L_2$ matrix. Let $U = [u_1 \ldots u_M] \in \mathbb{C}^{J_1 \times M}$ and $Z = [z_1 \ldots z_M] \in \mathbb{C}^{J_1 \times M}$. Then, it can be shown that

$$Z = \Phi A + U,$$ 

(21)

where $A = [a_1 \ldots a_M]$ is a row-sparse matrix [17], [38], [39]. As a result, finding the non-zero rows which is equivalent to the detection of transmitted preambles by type-2 devices is a multiple measurement vectors (MMV) problem.

There have been a number of approaches and algorithms proposed to solve MMV problems. In general, their complexity increases with the number of columns of $\Phi$, $L_2$. In addition, for a fixed row-sparsity, a better performance is achieved with a smaller number of columns, $L_2$. Thus, although a large $L_2$ is desirable for a low probability of preamble collision, it is necessary to keep $L_2$ as small as possible so that the complexity of algorithms is sufficiently low with good performance.

C. CAVI Algorithm for Low-Complexity Detection

There are a number of approaches to MMV problems. Among those, to detect transmitted preambles by type-2 devices in this section, we consider an approach based on variational inference, namely the coordinate ascent VI (CAVI) algorithm [40], [41], which has been successfully used in [21] to detect sparse signals in MTC.

Let $b$ denote the binary vector of length $L_2$, where $b_l = 1$ if $c_l$ is transmitted and 0 otherwise. Here, $b_l$ is referred to as the activity variable. Then, $a_m$ in (19) can be represented as

$$a_m = \sqrt{P_2} W_m b,$$ 

(22)

where $W_m$ is a diagonal matrix. To see the elements of $W_m$, consider the variance of $s_{m,l}^*$. For $l \in J_2$, $s_{m,l}^*$ is a zero-mean CSCG random variable according to the assumption of A1 and (2). In addition, its variance becomes 1 if only one type-2 device chooses $c_l$. If more devices choose $c_l$, the variance increases. Thus, we have

$$\text{Var}(s_{m,l}) = E[K_2,l | K_2,l \geq 1], \quad l \in J_2,$$ 

(23)

which is denoted by $\sigma_s^2$. Let

$$W_m[l] = \left\{ \begin{array}{ll} \sqrt{P_2 s_{m,l}^*} & \text{if } l \in J_2 \\ CN(0, P_2 \sigma_s^2) & \text{o.w.} \end{array} \right.$$ 

(24)
so that (22) is valid. Clearly, the diagonal elements of \( \mathbf{W}_m \)
in (24) are iid and CSCG. Then, \( z_m \) in (18) can also be expressed as
\[
\mathbf{z}_m = \Phi \mathbf{W}_m \mathbf{b} + \mathbf{u}_m,
\]
which can be characterized as the following CSCG random vector:
\[
\mathbf{z}_m \sim \mathcal{CN}(0, P_2 \sigma_2^2 \Phi \text{diag}(\mathbf{b}) \Phi^H + N_0 \mathbf{I}), \quad m = 1, \ldots, M.
\]

(26)

Note that in (26), \( \sigma_2^2 \) is to be decided. Suppose that the number of active type-2 devices, \( K_2 \), follows a Poisson distribution with mean \( \lambda_2 \). Since each active type-2 device chooses one of \( L_2 \) preambles uniformly at random, \( K_2, l \) becomes a Poisson random variable with mean \( \frac{\lambda_2}{L_2} \), i.e.,
\[
K_2, l \sim \text{Pois} \left( \frac{\lambda_2}{L_2} \right).
\]

Then, it can be shown that
\[
E[K_{2,l} | K_{2,l} \geq 1] = \frac{\sum_{e=1}^{\infty} k \left( \frac{\lambda_2}{L_2} \right)^k e^{-\frac{\lambda_2}{L_2}}}{\Pr(K_{2,l} \geq 1)} = \frac{\lambda_2 / L_2}{1 - e^{-\frac{\lambda_2}{L_2}}}.
\]

(27)

If \( \frac{\lambda_2}{L_2} \to 0 \), we can see that \( E[K_{2,l} | K_{2,l} \geq 1] \to 1 \). That is, for a sufficiently small \( \frac{\lambda_2}{L_2} \to 0 \), \( \sigma_2^2 \) can be set to 1.

Consequently, the detection of the transmitted preambles by type-2 devices can be carried out by the following maximum a posteriori probability (MAP) approach [13]:
\[
\hat{\mathbf{b}} = \arg \max_{\mathbf{b} \in \mathcal{B}} \Pr(\mathbf{b} | \{\mathbf{z}_m\}) = \arg \max_{\mathbf{b} \in \mathcal{B}} \prod_m f(\mathbf{z}_m | \mathbf{b}) + \Pr(\mathbf{b}),
\]

(28)

where \( \mathcal{B} = \{ \mathbf{b} | |\mathbf{b}| \in \{0, 1\} \} \). In (28), the activity variables, which are binary random variables, are to be detected. If an exhaustive search is considered, the complexity is proportional to \( |\mathcal{B}| = 2^{L_2} \). To avoid this, we can consider the variational distribution for each \( b_i \), denoted by \( \psi_i(b_i) \), and solve the following optimization problem:
\[
\psi^*(\mathbf{b}) = \arg \min_{\psi(\mathbf{b}) \in \Psi} D(\psi(\mathbf{b}) || \Pr(\mathbf{b} | \{\mathbf{z}_m\})),
\]

(29)

where \( \psi(\mathbf{b}) = \prod_m \psi(m) \) and \( \Psi \) represents the collection of all the possible distributions of \( \mathbf{b} \). Here, the KL divergence is given by
\[
D(\psi(\mathbf{b}) || f(\mathbf{b})) = \sum_{\mathbf{b}} \psi(\mathbf{b}) \ln \frac{\psi(\mathbf{b})}{f(\mathbf{b})},
\]

where \( f(\mathbf{b}) \) is any distribution of \( \mathbf{b} \) with \( f(\mathbf{b}) > 0 \) for all \( \mathbf{b} \in \mathcal{B} \). In (29), clearly, we attempt to find \( \psi(\mathbf{b}) \) that is close to the a posteriori probability, \( \Pr(\mathbf{b} | \mathbf{y}) \), as an approximation.

In [41], the minimization of the KL divergence is equivalent to the maximization of the evidence lower bound (ELBO), which is given by
\[
\text{ELBO}(\psi) = E[\ln f(\{\mathbf{z}_m\}, \mathbf{b})] - E[\ln \psi(\mathbf{b})].
\]

Since \( E[K_{2,l} | K_{2,l} \geq 1] \) in (27) increases with \( \frac{\lambda_2}{L_2} (\geq 0) \), its minimum is 1.

Let \( \mathbf{b}_{-l} = [b_1 \ldots b_{l-1} b_{l+1} \ldots b_{L_2}]^T \) and \( \psi_{-l}(\mathbf{b}_{-l}) = \sum_{i \neq l} \psi_i(b_i) \). The CAVI algorithm [40], [41] is to update one variational distribution at a time with the other variational distributions fixed (so that the ELBO can be minimized through iterations) as follows:
\[
\psi^*_l(b_l) \propto \theta_l(b_l) \triangleq \exp \left( E_{-l} \ln f(b_l | \mathbf{b}_{-l}, \{\mathbf{z}_m\}) \right),
\]

(30)

where \( E_{-l} [\cdot] \) represents the expectation with respect to \( \mathbf{b}_{-l} \) or with the distribution \( \psi_{-l}(\mathbf{b}_{-l}) \). Let \( \psi_l^{(t)} \) denote the \( t \)-th estimate of \( \psi_l \). In the CAVI algorithm, \( \psi_l^{(t)} \) is updated from \( l = 1 \) to \( L_2 \) in each iteration. The number of iterations is denoted by \( N_{\text{run}} \). Unfortunately, the convergence behavior of the CAVI algorithm is not known [41] and \( N_{\text{run}} \) can be decided through experiments [21].

Note that thanks to the Gaussian distribution of \( \{\mathbf{z}_m\} \), it is possible to find a closed-form expression for \( \theta_l(b_l) \) in (30), which can be found in [21].

There are a few remarks as follows.

- In general, it is not easy to find the performance of preamble detection when preambles are not orthogonal, which implies that the performance cannot be guaranteed in terms of the probabilities of MD and FA. On the other hand, as shown in Section IV, in RALP, at least, it is possible to guarantee certain performance in terms of the probabilities of MD and FA for type-1 devices thanks to their orthogonal preambles, \( \mathcal{L}_1 \). From this, resource allocation and barring schemes can be used to keep QoS requirements for type-1 devices.

- It is noteworthy that the approach in [28], which supports different priorities through dynamic allocation of preambles, does not take into account MD events that incur re-transmissions like preamble collisions. Since the probability of MD is not negligible with non-orthogonal preambles as will be shown in Section VI, it is required to take into account both the probabilities of preamble collision and MD so that guaranteed access delay can be ensured. However, as mentioned earlier, with non-orthogonal preambles, it is difficult to find the probability of MD. To keep the probability of MD negligible, the approach in [28] can only be used with orthogonal preambles, which however limits the number of devices to be supported.

- The overall complexity of signal detection at the BS can be divided into parts. The first is to detect type-1 devices. Since a bank of \( L_1 \) correlators is used as in (4), the complexity is \( O(M L_1 N^2) \). The second is to perform the CAVI algorithm to detect type-2 devices. It can be shown that the complexity of the CAVI algorithm per iteration is \( O(M L_2 N^2) \) [21]. As a result, the total complexity is \( O(M (L_1 + L_2) N^2) \) if the number of iterations for the CAVI algorithm is fixed (usually 5 iterations are sufficient).

VI. SIMULATION RESULTS

In this section, we present simulation results under the assumption of A1) with Alltop sequences of length \( N \in \{13, 37\} \). In order to focus on the probabilities of MD and
type-2 devices, of active type-1 devices as functions of the number of active devices, \( K \), when \( K_1 = 2 \), \( N = L_1 = 13 \), \( L_2 = 5N \), \( M = 10 \), \( P_1 = 12 \text{ dB} \), \( P_2 = 6 \text{ dB} \), and \( \epsilon \in \{10^{-2}, 10^{-3}\} \).

FA as performance criteria, no preamble collisions are taken into account with fixed \( K_1 \) and \( K_2 \) (i.e., it is assumed that each active device chooses a unique preamble with \( K_i \leq L_i \)).

### A. Performance of Type-1 Preamble Detection

In this subsection, the performance of of type-1 preamble detection is shown with the probabilities of MD and FA. As in (10), \( \tau_1 \) is decided to keep the probability of MD to be equal to or less than \( \epsilon \).

Fig. 4 shows the probabilities of (preamble detection) errors of active type-1 devices as functions of the number of active type-2 devices, \( K_2 \), when \( K_1 = 2 \), \( N = L_1 = 13 \), \( L_2 = 5N \), \( M = 10 \), \( P_1 = 12 \text{ dB} \), \( P_2 = 6 \text{ dB} \), and \( \epsilon \in \{10^{-2}, 10^{-3}\} \).

With \( P_{MD} = \epsilon \), it is shown that \( P_{FA} \) increases with \( K_2 \) (due to the increase of the interference, \( I_2 \)). In addition, with a lower \( \epsilon \), \( P_{FA} \) becomes higher. We can also see that the theoretical results (obtained from (9)) agree with the simulation results, which is an important observation as certain performance can be guaranteed for type-1 devices by deciding key parameters using the known distribution of \( Z = \|g\|_2^2 \) in (7).

In Fig. 5, the probabilities of (preamble detection) errors of active type-1 devices are shown as functions of the number of antennas, \( M \), at the BS when \( K_1 = 2 \), \( L_2 = 5N \), \( P_1 = 12 \text{ dB} \), \( P_2 = 6 \text{ dB} \), and \( \epsilon = 10^{-2} \) for small (i.e., \( N = 13 \)) and large (i.e., \( N = 37 \)) systems. Clearly, a better performance can be achieved with more antenna elements at the BS, which is predicted by (13), i.e., the probability of FA decreases exponentially with \( M \). Note that in Figs. 5 (a) and (b), we have \( \frac{K_2}{N} = \frac{10}{13} \) and \( \frac{K_2}{N} = \frac{30}{37} \) respectively. Thus, \( I_2 \) is almost the same, which leads to almost identical performance regardless of \( N \) in Figs. 5 (a) and (b).

Fig. 6 shows the probabilities of (preamble detection) errors of active type-1 devices as functions of the receive power when \( (K_1, K_2) = (2, 5) \), \( N = L_1 = 13 \), \( L_2 = 5N \), \( M = 10 \), and \( \epsilon = 10^{-2} \). In particular, in Fig. 6 (a), with a fixed \( P_2 \) (i.e., \( P_2 = 6 \text{ dB} \)), it is shown that the probability of FA decreases with \( P_1 \). In Fig. 6 (b), with a fixed \( P_1 \) (i.e., \( P_1 = 12 \text{ dB} \)), due to the increase of the interference power, the probability of FA increases with \( P_2 \). Thus, with a target probability of FA, for a given \( P_2 \) (or \( P_1 \)), \( P_1 \) (or \( P_2 \), respectively) can be decided.

### B. Performance of Type-2 Preamble Detection

In this subsection, we present simulation results of the type-2 preamble detection using the CAVI algorithm in Subsection V-C with 5 iterations. To see the impact of error propagation due to MD and FA events in the type-1 preamble detection, we consider two different cases: \( i \) on preamble in \( J_1 \) is incorrectly detected (i.e., an event of FA); \( ii \) one preamble in \( J_1 \) is not detected (i.e., an event of MD). As mentioned earlier, it is expected that the performance degradation due to an event of MD in the type-1 preamble detection is worse than that due to an event of FA.
Furthermore, we assume that the BS knows the number of active type-2 devices, \( K_2 \). Thus, we only consider the number of MD events, which is the same as that of FA events, and present the probability of MD to see the performance of type-2 preamble detection.

Fig. 7 shows the probabilities of MD of active type-2 devices with/without error propagation (due to FA and MD in the type-1 preamble detection) as functions of the number of active type-2 devices, \( K_2 \), when \( M = 10 \), \( P_1 = 12 \) dB, and \( P_2 = 6 \) dB. In particular, in Fig. 7 (a), the performance of a small system with \( N = L_1 = 13 \) and \( L_2 = 5N \) is shown, while in Fig. 7 (b), that of a large system with \( N = L_1 = 37 \) and \( L_2 = 5N \) is shown. As expected, the performance degradation due to an event of MD in the type-1 preamble detection is worse than that due to an event of FA. We also see that a large system (i.e., \( N = 37 \)) provides a better performance than a small system (i.e., \( N = 13 \)), which is well-known in the context of CS [17]. Note that this is not the case of the type-1 preamble detection, which was shown in Fig. 5.

In Fig. 8, the probabilities of MD of active type-2 devices with/without error propagation are shown as functions of the antennas at the BS, \( M \), when \( K_2 = 5 \), \( N = L_1 = 13 \), \( L_2 = 5N \), \( P_1 = 12 \) dB, and \( P_2 = 6 \) dB. Similar to Fig. 5, it is shown that a better performance can be achieved as \( M \) increases.

Fig. 9 shows the probabilities of MD of active type-2 devices with/without error propagation as functions of the receive power of type-1 devices, \( P_1 \), when \( K_2 = 5 \), \( N = L_1 = 13 \), \( L_2 = 5N \), \( M = 10 \), and \( P_2 = 6 \) dB. Clearly, the performance with error propagation due to an MD event in the type-1 preamble detection becomes worse as \( P_1 \) increases, while that due to an FA event is independent of \( P_1 \) as any signal in the subspace corresponding to the related preamble in \( L_1 \) is suppressed. This demonstrates that it is important to minimize the probability of MD in the type-1 preamble detection to keep a reasonable performance of type-2 preamble detection.

It is expected that the probability of preamble collision decreases with \( L_2 \) when \( K_2 \) is fixed. However, if \( L_2 \) increases, the complexity of the CAVI algorithm increases and its performance is also degraded. To see the impact of \( L_2 \) on the performance of the type-2 preamble detection, we show the probabilities of MD of active type-2 devices with/without error propagation in Fig. 10 as functions of the size of the preamble pool for type-2 devices, \( L_2 \), when \( K_2 = 5 \), \( N = L_1 = 13 \), \( M = 10 \), \( P_1 = 12 \) dB, and \( P_2 = 6 \) dB. As expected, the probability of MD increases with \( L_2 \). From this, we can see that there is a trade-off between the probability of preamble
collision and the probability of MD, and $L_2$ should be chosen for a balanced performance in terms of both probabilities.

From Figs. 4-10, it can be shown that the probabilities of errors (i.e., MD and FA) with orthogonal preambles (for type-1 devices) can be not only well predicted, but also higher than those with non-orthogonal preambles (for type-2 devices). Thus, in RALP, $L_1$ can be used for delay-sensitive devices, while $L_2$ for delay-tolerant devices.

VII. CONCLUDING REMARKS

In this paper, we proposed RALP using the notion of power-domain NOMA to support two different types of devices, namely type-1 devices (or delay-sensitive devices) and type-2 devices (or delay-tolerant devices) with one RB for high spectral efficiency. Low-complexity detection methods have been studied to detect transmitted preambles. Thanks to the orthogonality of the preambles for type-1 devices, it was possible to find closed-form expressions for the probabilities of detection errors, which can be used to determine key parameters for target probabilities of errors. This has been an important feature as a certain performance guarantee can be ensured with known probabilities of errors for type-1 devices.

Since we mainly focused on RALP in terms of the performance of the physical layer, resource allocation and barring schemes with RALP are not studied, which would be the topics to be investigated in the future.

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