Compressive Random Access Using A Common Overloaded Control Channel

Gerhard Wunder\textsuperscript{1}, Peter Jung\textsuperscript{2} and Mohammed Ramadan\textsuperscript{3}

\textsuperscript{1}Fraunhofer Heinrich-Hertz-Institut, Berlin (gerhard.wunder@hhi.fraunhofer.de)
\textsuperscript{2}Technische Universität Berlin (peter.jung@tu-berlin.de)
\textsuperscript{3}Fraunhofer Heinrich-Hertz-Institut, Berlin (mohammed.ramadan@hhi.fraunhofer.de)

\begin{abstract}
We introduce a “one shot” random access procedure where users can send a message without a priori synchronizing with the network. In this procedure a common overloaded control channel is used to jointly detect sparse user activity and sparse channel profiles. The detected information is subsequently used to demodulate the data in dedicated frequency slots. We analyze the system theoretically and provide a link between achievable rates and standard compressing sensing estimates in terms of explicit expressions and scaling laws. Finally, we support our findings with simulations in an LTE-A-like setting allowing “one shot” sparse random access of 100 users in 1ms.
\end{abstract}

I. INTRODUCTION

Sporadic traffic generating devices, e.g. machine-type communication (MTC), are most of the time irregular but regularly access the Internet for minor/incremental updates with no human interaction \cite{1}. Sporadic traffic will dramatically increase in the 5G market and, obviously, cannot be handled with the bulky 4G random access procedures. Two major challenges must be addressed: 1) unprecedent number of devices asynchronously access the network over a limited resource and 2) the same resource carries control signalling and payload. Dimensioning the control channels according to classical theory results in a severe waste of resources which, even worse, does not scale towards the requirements of the IoT. On the other hand, since typically user activity, channel profiles and message sizes are compressible within a very large receive space, sparse signal processing methodology is a natural framework to tackle the sporadic traffic.

Preliminary Work. The key findings of sparse signal processing are that in an under-determined system undergoing noise the signal components can be indeed identified if 1) the measurements are suitably composed and 2) the signal space is sparse (or more generally "structured"), i.e. only a limited number of elements in some given basis are non-zero. It has then soon been recognized that this can be exploited for multiple access with sparse user activity (see \cite{2} for a recent overview). This was extended to asynchronous fading channels \cite{3} as well as asynchronous multipath block fading channels with known/unknown (sparse) multipath channel \cite{4}. Notably, all these concepts are fundamentally different from a classical "overloaded" CDMA channel without sparsity \cite{5} where user activity and data detection are separate steps.

Recently, massive MTC random access for 5G has fuelled the topic, particularly within the EU projects METIS and 5GNOW \cite{6}, \cite{7}, \cite{8}. Ref. \cite{6} investigates the interaction of advanced multiuser detection and a random access scheme called coded slotted ALOHA. However, the effect of channel estimation and data detection errors (which is necessary due to broadband) and error propagation in the interference cancellation scheme is crucial \cite{6} and must be carefully considered in follow-up work. In \cite{9} new coding schemes and limits for MTC with random arrivals in a slotted ALOHA (using either time or frequency slots) have been presented. While narrowband in nature and without advanced sparsity promoting multiuser detection, it is argued that for such scenarios the effect of channel estimation errors becomes negligible (however, implicitly, by using arbitrary long preambles!). Consequently, recent concepts deal either with data or channel estimation and an overall architecture which includes identification, channel estimation, asynchronicity and data detection in "one shot" is an open topic.

Contributions. In this paper, we propose a ALOHA (OFDMA protocol similar to \cite{9}) where users select frequency slots of flexible size without coordination. In such asynchronous scenario, it becomes very inefficient to reserve control resource for every slot since delay spread is large, i.e. coherence bandwidth is small. We suggest an overloaded common control channel which is accessed by all active users at the same time. Spars signal processing will be used for joint (sparse) user activity detection and (sparse) channel estimation. One control channel concept is that data and control channels are superimposed so that control is spread over the whole signal space and collected back within some (small) observation window \cite{8}. Another concept which is followed here is to fully separate control and data which requires a careful investigation of actual payload vs. control signaling ratio. The different concepts are depicted in Fig\textsuperscript{1}

In the following sections the details of such sparsity aware random access scheme are outlined, analyzed and simulated.

Notations. $\|x\|_{\ell_q} = (\sum_{i} |x_i|^q)^{1/q}$ is the usual notion of $\ell_q$-norms and $\|x\| = \|x\|_{\ell_2}$, denote with supp$(x) := \{ i : x_i := (\epsilon_i, x) \neq 0 \}$ the support of $x$ in a given fixed (here canonical) basis $\{ \epsilon_i \}_{i=1}^{\infty}$. The size of its support is denoted as $\|x\|_{\ell_0} := \text{supp}(x)$. $W$ is the (unitary) Fourier matrix with

Gerhard Wunder is also with the Technische Universität Berlin. This work was carried out within the 5GNOW project, supported by the European Commission within FP7 under grant 318555, and within DFG grants WU 598/3-1. Peter Jung was supported by DFG grant JU-2795/2.
elements \((W)_{kl} = n^{-\frac{1}{2}} e^{-i2\pi kl/n}\) for \(k, l = 0 \ldots n - 1\), hence, \(W^{-1} = W^*\) where \(W^*\) is the adjoint of \(W\). We use here also \(\hat{x} = Wx\) to denote Fourier transforms and \(\circ\) means point-wise product. \(I_n\) is the identity matrix in \(\mathbb{C}^n\), \(\text{diag}(x)\) is some arbitrary diagonal matrix with \(x \in \mathbb{C}^n\) on its diagonal.

II. COMPRESSIVE RANDOM ACCESS

A. "One-shot" transmitter

Let \(p_u \in \mathbb{C}^n\) be an pilot (preamble) sequence from a given (random) set \(P \subset \mathbb{C}^n\) and \(x_u \in \mathbb{C}^n\) be an unknown (uncoded) data sequence \(x_u \in \mathcal{X}^n \subset \mathbb{C}^n\) both for the \(u\)-th user with \(u \in \{1, \ldots, U\}\) and \(U\) is the (fixed) maximum set of users in the systems. Note that in our system \(n\) is a very large number, e.g. 24k. Provided user \(u\) is active we set:

\[
\alpha := \frac{1}{n} \|p_u\|^2 \quad \text{and} \quad \alpha' := 1 - \alpha = \frac{1}{n}E\|x_u\|^2
\]

If a user is not active then we set both \(p_u = x_u = 0\), i.e. either a user is active and seeks to transmit data or it is inactive. Hence, the control signalling fraction of the power is \(\alpha\) and, due to the random zero-mean nature of \(x_u\), we have \(\frac{1}{n}E\|p_u + x_u\|^2 = 1\), i.e. the total transmit power is unity.

We will use a cyclic model, which is achieved with OFDM-like signaling and the use of an appropriate cyclic prefix and restrict our model here to time-invariant channels. Each vector \(h_u \in \mathbb{C}^{T_c}\) denotes the sampled channel impulse response (CIR) where \(T_c\) is the length of the cyclic prefix. We assume to have a priori support knowledge on each \(h_u\); (i) bounded support, i.e. \(\text{supp}(h_u) \subseteq [0, \ldots, T_c - 1]\) due to the cyclic prefix and (ii) sparsity, i.e. \(\|h_u\|_0 \leq k_1\). Eventually, we assume that only \(k_2\) users out of \(U\) in total are actually active. Define \(k := k_1k_2\).

In an OFDM system the FFT size \(n\) is then chosen as \(n \gg T_c\). Let \([h, 0] \in \mathbb{C}^n\) denote the zero-padded CIR. With these assumptions the received signal is then:

\[
y = \sum_{u=0}^{U-1} \text{circ}([h, 0])(p_u + x_u) + e
\]

\[
y_{B} = \Phi_{B} y
\]

where \(e\) and \(\hat{e}\) are statistically equivalent.

For the users’ data the entire bandwidth \(B_C\) is dived into \(B\) frequency slots. A standard assumption is that users’ arrivals are modeled as a Poisson process with rate \(\lambda\) which is even true if retransmissions are incorporated. Each user selects a slot in an ALOHA (O)FDMA fashion. Clearly, by the single interval contention period the users will choose the same FDMA slot with some probability, called outage event. Obviously, for a fixed rate \(R\) requirement throughput maximization means outage probability minimization. Define the order user rates as \(R_1, R_2, \ldots, R_U\). Then, it is shown in \cite{9} that the average throughput (for any user \(k\)) is given by:

\[
T(\lambda, R) = \frac{\exp\left(-\frac{\lambda}{R}ight) \cdot \Pr(R_k > R)}{T_s}
\]

with a rate constraint \(R\) and a slot duration \(T_s\). In the following we assume that the probabilities \(\Pr(R_k > R)\) are mainly dependent on the receive powers (user position, slow fading effects) while the fast fading effects are averaged out due to coding over subcarriers. Hence, user rates are ergodic and are calculated as expectations over the fading distributions. The relevant expressions under erroneous channel estimation will be provided in this paper.

B. Receiver operations

All performance indicators depend on the number of subcarriers in \(B\) (control) and \(B_C\) (data). The goal is the limitation to a small observation window \(B\). Let \(P_B : \mathbb{C}^n \rightarrow \mathbb{C}^m\) be the corresponding projection matrix, i.e. the submatrix of \(I_n\) with rows in \(B\). For identifying which preamble is in the system we can consider \(\tilde{y}\) and use the frequencies in \(B\), i.e. \(\Phi_B = P_B W\), so that:

\[
y_B := P_B \sum_{u=1}^{U} \left[\sqrt{n}h_u \circ (\hat{p}_u + \hat{x}_u)\right] + P_B \hat{e}
\]
Notably in [8] we have introduced randomized pointwise multipliers $\xi \in \mathbb{C}^n$ in time domain instead, denoted by the corresponding $n \times n$ diagonal matrix $M_\xi := \text{diag}(\xi)$, which is favorable for the sparse recovery. Hence, the $m \times n$ sampling matrix $\Phi_B = P_B W M_\xi$ is considered which, however, comes at the cost of performance loss due to superimposed pilot subcarriers.

For algorithmic solution, we can stack the users as:

$$y = \sum_{u=1}^{U} \mathbf{circ}(h_u)(p_u + x_u) + e = D(p)h + C(h)x + e$$

where $D(p) := [\mathbf{circ}(p_1), \ldots, \mathbf{circ}(p_U)] \in \mathbb{C}^{n \times U \times m}$ and $C(h) := [\mathbf{circ}([h_{10}], \ldots, \mathbf{circ}([h_{U0}])] \in \mathbb{C}^{n \times U \times n}$ are the corresponding compound matrices, respectively $p = [p_1^T \ p_2^T \ \ldots \ p_u^T]$, $h = [h_1^T \ h_2^T \ \ldots \ h_U^T]$ are the corresponding compound vectors. If we assume each user-channel vector $h_u$ to be $k_1$-sparse and $k_2$ active then $h$ is $k$-sparse.

For joint user activity detection and channel estimation exploiting the sparsity we can use the standard basis pursuit denoising (BPDN) approach:

$$\hat{h} = \arg \min_{h} \|h\|_1, \quad \text{s.t.} \quad \|\Phi_B D(p)h - y\|_2 \leq \epsilon$$

Moreover, several greedy methods exists for sparse reconstruction. In particular, for CoSAMP [10] explicit guarantees in reconstruction performance are known and can be used instead of BPDN. After running the algorithm in eqn. (4) the decision variables $\|h_u\|_{l_2}$, $\forall u$, are formed, indicating that if $\|h_u\|_{l_2} > \xi$ where $\xi > 0$ is some predefined threshold the user is considered active and its corresponding data is detected. In [8] the correponding pilot signal is subtracted from the received signal by interference cancellation. Here, we assume full separation of data and control so that $\text{supp}(p_u) \subseteq B \ \forall u$. Denote the error of this operation as $d := h - \hat{h}$. Hence, the received signal is given by:

$$\hat{y} = (\sqrt{\alpha}h + \hat{d}) \odot \hat{x} + \hat{e}$$

which a set of parallel channels each with power $E(\|\hat{x}_k\|^2) = 1 - \alpha$, $|\hat{p}|^2 = \alpha$ and $E(|\hat{x}_k|^2) = \sigma^2$.

### III. PERFORMANCE ANALYSIS

It is possible to find the scaling of rates if one makes the following assumptions: (i) all users employ independent Gaussian codebooks (ii) if a user is not detected the corresponding data is discarded (iii) if RIP is not satisfied, i.e. $\delta_{2k} > \delta$ for given $\delta$ then the data of all is fully discarded (iv) if the actual noise vector is larger than the estimated noise vector then the data of all is discarded. In our analysis we will work with outage probabilities for (i) and (ii). Refined estimates which include (iii) and (iv) require more assumptions on the sampling model, noise distribution and recovery procedure and will therefore appear in a separate work.

### A. RIP and performance guarantees

Let $\Sigma_k := \{x \in \mathbb{C}^n : \|x\|_{l_0} \leq k\}$ denotes the $k$-sparse vectors. There is a well-known result [11] on BPDN and we call this as the $Q_1$-estimator for $x$ given $y$, i.e. $\hat{x} = Q_1(y)$: if $\Phi_B$ is $2k$-RIP with $\delta_{2k} < \sqrt{2} - 1$ and $\|e\|_2 \leq \epsilon$ then:

$$\|Q_1(\Phi x + e) - x\|_2 \leq c_1 \epsilon$$

with $c_1 = 4\sqrt{1 + \delta_{2k}}/\sqrt{\delta_{2k}}$ (in particular, for $\delta_{2k} = \frac{1}{2}$ this gives $c_1 = 8.5$). It is known that $\delta_{2k} \leq \sqrt{2} - 1$ is a necessary condition. In [12] the bound has been improved to $\delta_{2k} \leq 3/(4 + \sqrt{6}) \approx 0.4652$. Similar bound exists for CoSAMP [10], i.e. $\delta_{4k} \leq \sqrt{2/5 + \sqrt{3}} \approx 0.3843$ [13].

Up this point we have mentioned uniform reconstruction guarantees (for any $x$) for a given matrix $\Phi$ and these are related to its RIP-constant $\delta_{2k}$. It is still difficult to constructively design measurements matrices with sufficiently small RIP constants. In this paper we use the results in [14]: For any unitary matrix $U$, the measurement matrix $P_B \cdot U$ with $B$ chosen uniformly at random with cardinality $m$ such that:

$$m \geq c \delta^{-2} \mu^2 k \log^5(n)$$

has RIP with probability $\geq 1 - e^{c' n^{-1}}$ and $\delta_{2k} \leq \delta$, where $\mu = \mu(U, Id)$ is the incoherence between $U$ and the identity (standard basis).

### B. User detection

Let us first calculate the probability of not detecting an active user $P_{md}(\xi)$ ("missed detection"), and falsely detecting an inactive user $P_{fa}(\xi)$ ("false alarm"). Recall that for a given pilot power $\alpha$ the channel estimation error is $d = h - \hat{h}$ with $\hat{h} = Q_1(y/\sqrt{\alpha})$.

**Theorem 1.** We have for a fixed sampling matrix $\Phi$ with RIP-constant $\delta_{2k}$:

$$P_{md}(\xi) \leq F(\xi) \leq \frac{c_r(\xi) c_1(\delta_{2k})^2 m \sigma^2}{\alpha k_2}$$

$$P_{fa}(\xi) \leq \frac{c_1(\delta_{2k})^2 m}{\alpha \xi \sigma^2}$$

where $c_r(\xi)$ is defined below in (7).

**Proof:** Since the system is symmetric we can consider any user $u$ and drop the indices $(\cdot)_u$ in all user–specific variables. Furthermore, we also drop $\circ$ used to denote Fourier transforms. Abbreviate the dependent random variables by $x := \|h\|$ and...
\[ y := \|d\| \text{ and let } F(x) \text{ be the distribution of } x. \text{ We have:} \]

\[ \Pr \{ \| h \| < \xi \} = \Pr \{ \| h - h + h \| < \xi \} \leq \Pr \{ x - \xi < y \} \]

\[ = \Pr \{ x - \xi < y \} \cap \{ x < \xi \} + \Pr \{ x - \xi < y \} \cap \{ x \geq \xi \} \]

\[ \leq \Pr \{ x < \xi \} + \Pr \{ x - \xi < y \} \cap \{ x \geq \xi \} \]

\[ = \Pr \{ x < \xi \} + \Pr \{ y^2 > (x - \xi)^2 \} \cap \{ x \geq \xi \} \]

\[ \leq \int_0^\xi dF(x) + \int_\xi^\infty \frac{E(y^2 | x)}{(x - \xi)^2} dF(x) \]

\[ \leq F(\xi) + \frac{c_\alpha(\xi) E(\|d\|^2)}{k_2} \]

(8)

where in the last step we use Markov’s inequality and:

\[ c_\alpha(\xi) := \int_\xi^\infty \frac{dF(x)}{(x - \xi)^2} \]

(9)

and the last step follows since the \( \ell_2 \)-norm function is the sum of its squared terms. Hence, its expectation can be calculated as the expectation of the sum of partial user contributions. These partial user contributions depend only on the marginal distributions which are equal for all active users from which the result follows.

The term \( E(\|d\|^2) \) can be calculated as

\[ E(\|d\|^2) = E(\|Q_1(y/\sqrt{\alpha}) - h\|^2) \]

\[ \leq \frac{c_1(\delta_{2k})^2}{\alpha} E(\|e\|^2) \]

\[ \leq \frac{c_1(\delta_{2k})^2 m \sigma^2}{\alpha} \]

The false alarm probability is calculated in a similar manner.

For the ergodic rates \( R(\alpha) := E \log(1 + (1 - \alpha) \| h \|^2) \)

per subcarrier with a random channel power \( \| h \|^2 \) for a given pilot/data power split \( \alpha \) we can show the following:

**Theorem 2.** Let the channel impulse response be \( k \)-sparse and use eqn. (4) as the channel estimate. The achievable rate \( R(\alpha) \) per subcarrier for a particular user is lower bounded by:

\[ R(\alpha) \geq E_{h\mid\|h\|<\xi} \left[ \log(1 + (1 - \alpha) \| h \|^2 \sigma^{-2}) \right] (1 - P_{\text{fail}}) \]

\[ - \log \left( 1 + \frac{(1 - \alpha) c_1(\delta_{2k})^2 m \sigma^2}{\alpha^2} \right) \]

for a fixed sampling \( \Phi \) obeying a RIP-constant \( \delta_{2k} < \sqrt{2} - 1 \).

To prove this theorem we need the following lemma:

**Lemma 1.** Suppose \( h, \tilde{h} \) are random variables and \( h \) is an estimate of \( h \) (hence they are correlated). Denote the error as \( d = h - \tilde{h} \) and its unbiased version \( d = d - E(d|h) \). Then we have:

\[ E \log (1 + \|h\|^2) \leq E \log (1 + \|h + E(d|h)\|^2 + E(\|d\|^2|h)) \]

**Proof:** We have:

\[ E \log (1 + \|h + E(d|h)\|^2 + E(\|d\|^2|h)) \]

\[ = E \log (1 + E(h + E(d|h)^2|h) + E(\|d\|^2|h)) \]

\[ = E \log (1 + E(h + E(d|h) + d)^2|h)) \]

\[ = E \log (1 + E(\|d\|^2|h)) \]

\[ \geq E \log (1 + \|h\|^2) \]

where the last line is due to Jenssen’s inequality.

**Corollary 1.** Note that Lemma 2 recovers Lemma 2 in [15, Theorem 1] by the fact that if \( h \) is the minimum mean squared estimate (MMSE) of \( h \) then \( E(d|h) = 0 \) so that \( d = 0 \) and \( h \) and \( d \) are actually independent. Hence \( E(\|d\|^2|h) = E(\|d\|^2) = \alpha \) and \( E(\|h\|^2) = 1 - \alpha \) so that:

\[ E \log (1 + \|h\|^2) \]

\[ \leq E \log (1 + \|h + E(d|h)\|^2 + E(\|d\|^2|h)) \]

\[ = E \log (1 + \|h + E(d|h)^2 + E(\|d\|^2|h)) \]

\[ = E \log (1 + \|h\|^2) \]

\[ = E \log (1 + (1 - \alpha) \|h\|^2 + \alpha) \]

because \( h \) and \( h \) have the same distribution.

**Proof of Theorem 2.** We have for each subcarrier and user (recall that we also dropped user indices \( (\cdot)_u \) and the \( \cdot \)-notation for the Fourier transform):

\[ y = (h + d)x + e \]

where \( x = \|x\|^2 = 1 - \alpha \) and \( E(\|e\|^2) = \sigma^2 \). We can assume that \( x \) is independent of the tuple \( (h, d) \) but \( h \) and \( d \) are in fact not (they were if we had MMSE estimation). Linking the achievable mutual information \( I \) to MSE estimation as [15, Theorem 1]

\[ I(x; y) = H(x|h) - H(x|h, y) \]

\[ \geq H(x|h) - E \left( \log P_e E(|x - \alpha y|^2 |h) \right) \]

where real \( \alpha \) is some free parameter. The optimal \( \alpha \) is the MMSE of \( x \) so that in general by the orthogonality principle:

\[ \hat{\alpha}_1 = E(yx^*|h)/E(|y|^2|h) \]

In the following we use \( \hat{\alpha}_1 \) for bounding the rate but without explicit calculating the term. Before we proceed let us rewrite

\[ y = (h + E(d|h) + d - E(d|h))x + e \]

\[ = (h + E(d|h) + d))x + e \]

where

\[ d = d - E(d|h) \]

Hence, we have \( E(d|h) = 0 \) so that \( h + E(d|h) \) and \( d \) are in fact orthogonal which is the desired goal. Using optimal \( \hat{\alpha}_1 \)
we have after some tedious algebra:

\[
R(\alpha) \\
\geq E \log \left( \frac{E(|x|^2)|h + E(d|h)|^2 + E(|x|^2)E(|d|^2|h) + \sigma^2}{E(|x|^2)E(|d|^2|h) + \sigma^2} \right) \\
= E \log \left( 1 + \frac{E(|x|^2)|h + E(d|h)|^2}{E(|x|^2)E(|d|^2|h) + \sigma^2} \right) \\
= E \log \left( 1 + \frac{(1 - \alpha)|h + E(d|h)|^2}{(1 - \alpha)E(|d|^2|h) + \sigma^2} \right)
\]

The capacity loss per subchannel in eqn. (5) can be upper-bounded by

\[
\Delta R(\alpha) \leq E \log \left( 1 + \frac{(1 - \alpha)E(|d|^2|h)}{\sigma^2} \right)
\]

which by virtue of Lemma 1 gives:

\[
\Delta R(\alpha) \leq E \log \left( 1 + \frac{(1 - \alpha)E(|d|^2|h)}{\sigma^2} \right)
\]

Clearly, we have \(E(|d|^2|h) \leq E(|d|^2|h)\) and get so the final result using:

\[
E(|d|^2|h) \leq 2E(|d|^2|h) \leq \frac{c_1(\delta_{2k})^2m\sigma^2}{\alpha n}
\]

We can finally incorporate the missed detection properly.

We also have the following upper bound (assuming nearest neighbor decoding) where the estimation error acts like an additional AWGN term.

**Theorem 3.** Let the channel impulse response be k-sparse and use eqn. (2) as the channel estimate. The achievable rate per subcarrier is upper bounded by:

\[
R(\alpha) \leq E_h \log \left( 1 + \frac{(1 - \alpha)h\sigma^{-2}}{1 + \frac{c_1(\delta_{2k})^2m\sigma^2}{\alpha n}} \right)
\]

for a fixed sampling \(\Phi\) obeying a RIP-constant \(\delta_{2k} < \sqrt{2} - 1\).

**Proof:** The prove follows from [1].

**IV. SIMULATIONS**

An LTE-A 4G frame consists of a number of subframes with 20MHz bandwidth; the first subframe contains the PRACH with one "big" OFDM symbol of 839 dimensions located around the frequency center of the subframe. The FFT size is 24578=24k corresponding to the 20MHz bandwidth whereby the remainder bandwidth outside PRACH (and subsequent sub-frames) is used for scheduled transmission in LTE-A, so-called PUSCH. The prefix of the OFDM symbol accommodates delays up to 100\(\mu\)s (or 30km cell radius) which equals 3000 dimensions. In the standard the RACH is responsible for user acquisition by correlating the received signal with preambles from a given set. Here, to mimic a 5G situation, we equip the transmitter with the capability of sending information in "one shot" in an extended PRACH (see Fig 4). Within extended PRACH a common control channel allows joint user activity detection and channel estimation according to our model.

In the setting, a limited number of users is detected out of a maximum set (here 10 out of 100). We assume that the delay spread is below 300 dimensions of which only a set of 6 paths are actually relevant. The pilot signalling is similar to [8] but modified to fit the data/pilot separation. Each active user sends 1000 bits in some predefined frequency slot. This is uniquely achieved by mapping the sequences to a slot. Hence, in the classical Shannon setting 100 users x (300 paths + 1000 bits) = 130k dimensions are needed while there are only 24k available! The performance results are depicted in Fig 2 where we show show symbol error rates (SER) over the pilot-to-data power ratio \(\alpha\). Moreover, in Fig 3 we depict false detection probability \(P_{FD}\) (some user is detected while not active) over missed detection probability \(P_{MD}\) (user is active while not detected). We observe that, although the algorithms might not yet capture the full potential of this idea, reasonable detection performance can be achieved by varying \(\alpha\). In the 4G LTE-A standard a minimum \(P_{FD} = 10^{-3}\) is required for any number of receive antennas, for all frame structures and for any channel bandwidth. For certain SNRs a minimum \(P_{MD} = 10^{-2}\) is required. It can be observed from the simulations that the requirements can be achieved. Actually, compared to 4G LTE-A where the control signalling can be up to 2000\% of a single resource element the control overhead is in the CS setting down to to 13\% (let alone the huge increase in latency) in the best case.
V. CONCLUSIONS

In this paper, we provided ideas how to enable random access for many devices in a massive machine-type scenario. In the conceptional approach as well as the actual algorithms sparsity of user activity and channel impulse responses plays a pivotal role. We showed that using such framework efficient "one shot" random access is possible.

VI. ACKNOWLEDGEMENTS

The work of G. Wunder was supported by the 5GNOW project supported by the European Commission under grant 318555 (FP7 Call 8). Peter Jung was supported by DFG-grant JU 2795/2-1. We also thank the reviewers for their comments.

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