DNN-based Active User Detection for an NB-IoT Compatible Grant Free NOMA System

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***Abstract*—Grant free non-orthogonal multiple access (GF-NOMA) is a promising access method for massive machine type communication (mMTC), which has several advantages when compared to the conventional grant based access method, such as, reduced latency, smaller scheduling and signalling overheads, and improved energy efficiency. Since there is no explicit grant given to each user in GF-NOMA, detecting all the active users present, i.e., active user detection (AUD) at the base station (BS) becomes crucial. Typically, AUD is performed using correlation with all possible preamble sequences transmitted by the GF-NOMA users. Recently, deep learning (DL) based models have emerged as a viable alternatives for AUD. However most of these works assume perfect timing and frequency synchronization of users, which hardly occurs in practice. In this work, a GF-NOMA scheme and a deep neural network (DNN) model for AUD are proposed. The proposed scheme is compatible with the narrowband Internet of things (NB-IoT) and the proposed DNN-based AUD mechanism accounts for the impact of timing and frequency offsets. It is demonstrated that the performance of proposed DNN based AUD scheme is comparable (or slightly better) than the conventional method while providing a significant reduction in the computational complexity.**

***Index Terms*—massive machine-type communication, non-orthogonal multiple access, Zadoff-chu sequence, timing offset, frequency offset, deep neural network, active user detection.**

I. Introduction

Due to an increase in the number of Internet of things (IoT) devices and their applicability in a variety of scenarios, massive machine type communications (mMTC) has received a lot of attention in the recent years. As the name suggests, mMTC is mainly concerned with the massive connectivity of a large number of devices (e.g., sensors, robots and vehicles) to the base station (BS). However, supporting mMTC is a challenge for the existing wireless communication standards [1], such as, long term evolution-MTC (LTE-M) and narrow-band Internet of things (NB-IoT) due to the heavy signaling overhead incurred in the scheduling process and the lack of time/frequency resources caused by the use of orthogonal multiple access. Therefore, *grant free (GF) access* and *non-orthogonal multiple access (NOMA)* have been proposed as candidate technologies for massive connectivity [2] [3]. A merger of these two technologies, called *GF-NOMA* is also being considered [4].

A GF access mechanism from a device consists of a preamble sequence followed by its data transmission. Specifically, in the case of GF-NOMA, these preambles correspond to one of the non-orthogonal sequences picked uniformly randomly from a predetermined set. Since each device transmits information without scheduling, a method for identifying the active devices (i.e., devices that are transmitting data) among all possible devices in a cell is necessary. This technique, often referred to as active user detection (AUD), is based on processing these non-orthogonal preamble sequences and is a critical step for successful data decoding in GF-NOMA [5].

In a typical mMTC scenario, only a small portion of devices will be active at a given time. Hence the AUD problem can be formulated as a sparse recovery problem and various techniques based on the compressed sensing (CS) have been proposed [6]–[8]. The basic idea behind these approaches is to process the correlation of the received signal and the possible preamble sequences for each device, such that, in each iteration, a device whose preamble sequence is maximally correlated with the received signal is chosen. Thus the AUD performance is dictated by cross-correlation properties of the preamble sequences and the CS based AUD schemes might not be effective when preamble sequences are highly correlated and/or when number of active users is high [9].

Recently, machine learning techniques like deep neural network (DNN) techniques have been employed for AUD, specifically for GF access systems [10]–[13]. For instance, the DNN architecture proposed in [10] is able to detect the active users given that there is a prior information about the number of active users present. The work in [13] introduces end-to-end neural networks that mimic noisy measurements and sparse recovery to jointly design the preamble matrix and the corresponding DNN based receiver. Different deep auto-encoder algorithms derived from CS-based algorithms which achieve highly accurate channel estimation and activity detection are proposed in [14]. These designs demonstrate the benefits of correctly choosing the preamble sequences to attain reasonable sparse recovery accuracy. However, these end-to-end networks are independent, clean-state solutions, which may be hard to integrate to the existing standardized IoT physical layer protocols like those in NB-IoT.

The main motivation behind this work is that the existing DNN-based methods assume perfect timing and frequency synchronization between the devices and the BS. This is highly unlikely in an mMTC scenario, since a bulk of these devices are low-complexity, low-cost IoT nodes. The main contributions of this paper are as follows:

- We propose a novel grant free random access scheme compatible with existing NB-IoT standard and supports

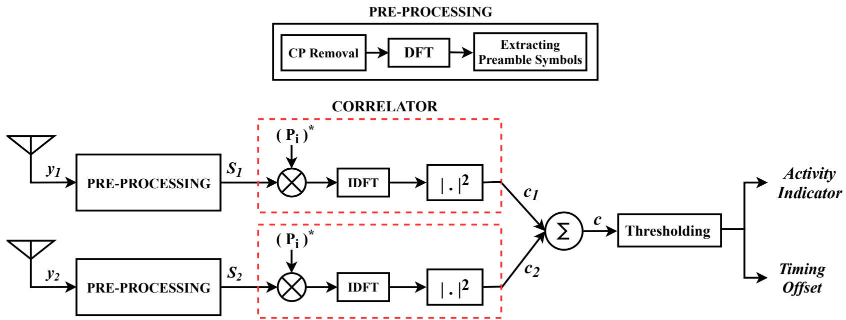


Fig. 1. Conventional receiver architecture for AUD. The "correlator" block will be replaced by the proposed DNN-based AUD.

higher user density than current narrowband physical random access channel (NPRACH) procedure in NB-IoT.

- We introduce a DNN architecture for AUD, which is applicable in practical GF-NOMA scenarios involving timing and frequency offsets.
- We demonstrate through simulations that the AUD performance of the proposed method is comparable (or slightly better) than the conventional correlation based AUD, while resulting in a significant reduction in the computational complexity.

II. System Model

We consider a typical uplink grant free system with one BS serving a total of M number of users. Let k denote the number of active users transmitting simultaneously and $\mathbb{P} = \{\mathrm{P}_1, \ldots, \mathrm{P}_\mathrm{N}\}$ denote the set of preamble sequences. As in an orthogonal frequency division multiple access (OFDMA) system, each active user transmits the preamble sequence in the frequency domain over multiple subcarriers and their corresponding time domain signal is obtained using inverse fast Fourier transform (IFFT). Then the signal transmitted by the i^{th} user is given by

$$x_i(n) = \frac{1}{N_{\text{FFT}}} \sum_{m=0}^{N_{\text{FFT}}-1} \mathrm{P}_\mathrm{i}(m) e^{j\frac{2\pi nm}{N_{\text{FFT}}}} \tag{1}$$

with $n = -N_{\text{CP}}, -N_{\text{CP}}+1, \ldots, 0, \ldots, N_{\text{FFT}}-1$, where N_{CP} and N_{FFT} are the cyclic prefix (CP) length and the fast Fourier transform (FFT) size, respectively. However, unlike the regular OFDMA system, all the users using GF access occupy the same set of subcarriers. Since there are k such users transmitting simultaneously, the received signal at the BS is given by

$$y(n) = \sum_{i=1}^{k} h_i e^{j2\pi r_i n} x_i(n - d_i) + w(n) \tag{2}$$

where the parameters h_i, r_i and d_i represent the channel coefficient (assuming flat-fading), the residual carrier frequency offset (RCFO) normalized by the system bandwidth and the timing offset of the i^{th} user, respectively. The term $w(n) \sim \mathcal{CN}(0, \sigma^2)$ represents the effect of additive white Gaussian noise (AWGN) at the BS.

The BS performs AUD on the received signal. In conventional correlation based AUD mechanism, the received signal is correlated with all possible preamble sequences. A predefined threshold is applied to the resultant correlation energy to obtain the constituent preamble sequences in the received signal as shown in Fig 1. In the process of user activity detection, two kinds of error may occur - a) false alarm and b) missed detection. A false alarm occurs when a device is marked to be detected even though it is not active and a missed detection occurs when we fail to detect an active device. Therefore, the threshold has to be chosen in such a way that it balances the trade-off between number of false alarms and missed detection. In the following, we describe the proposed GF-NOMA scheme and a DNN-based AUD mechanism for the same.

III. Proposed GF-NOMA Scheme and DNN-based AUD Mechanism

A. GF-NOMA scheme

In a typical mMTC scenario, the number of actively transmitting users is far less than total number of users. Hence we model the number of active users N_a as a Poisson random variable with mean λ[1]. The average success probability of all users in such a system is given by [15]

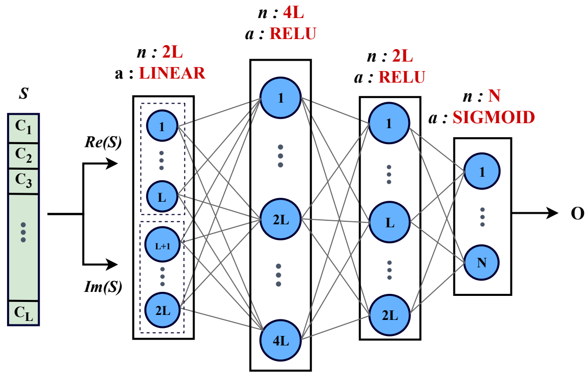
$$\mathbb{E}[p_{\text{all}}] = e^{-\lambda} \left(1 + \lambda / N_\mathrm{p}\right)^{N_\mathrm{p}} \tag{3}$$

The number of preamble sequences N_p required is chosen based on the desired average success probability of all users, which can be obtained using Eqn. (3) as

$$N_\mathrm{p} = \left\lceil \frac{\lambda^2}{2\log(1/\mathbb{E}[p_{\text{all}}])} \right\rceil \tag{4}$$

We model the GF access procedure in accordance with the "pre-configured resources" paradigm being considered in the subsequent releases of NB-IoT [16], where a predetermined set of time-frequency resources is reserved for contention based GF access. Moreover, this is similar to the NPRACH procedure currently being used by the NB-IoT devices to establish uplink

[1] Usually the number of active devices N_a in mMTC scenario is modelled as a binomial random variable $\mathcal{B}(N_\mathrm{a}; M, p)$, where M is the total number of devices in the system and p is the probability of each user being active. We know that Poisson distribution is a limiting case of binomial distribution when M is very large and p is small, which holds for mMTC scenarios.



DNN Training Parameters	
Loss function	Binary Cross Entropy
Optimizer	ADAM
Batch size	1024
Epochs	75
Learning rate	0.001

n : Number of Neurons
a : Activation Function

Fig. 2. Proposed DNN architecture for AUD in the NB-IoT Compatible GF-NOMA System.

synchronization. Also, we have considered Zadoff-Chu (ZC) sequences for preambles, which are widely employed in LTE and NB-IoT systems. The ZC sequences of length L generated using different roots have constant cross-correlation equal to $\sqrt{L}$ if the difference between the roots is relatively prime to L. Thus, if L is chosen to be a prime number, one can generate up to $N = (L-1)$ non-orthogonal sequences of length L.

In this work, the set of resources reserved for GF transmission is divided into T transmission opportunities (TOs) with N preamble sequences available in each TO. Given that we require N_{p} preamble sequences, the number of TOs and number of preambles per TO should satisfy the relation $NT \geq N_{\mathrm{p}}$. Also, users pick any one of the T TOs and any one of N available preamble sequences in each TO uniformly randomly. Thus, the number of users (k) in any given TO will be a binomial random variable with the probability mass function (PMF)

$$\mathrm{p}(k) = \binom{\lambda}{k}\left(\frac{1}{\mathrm{T}}\right)^{k}\left(1-\frac{1}{\mathrm{T}}\right)^{(\lambda-k)} \tag{5}$$

Note that a collision occurs when two or more users choose the same TO and the same preamble sequence. However, one can choose N_{p} such that collisions are minimal [15]. Thus we focus on performing AUD in non-collision scenarios using a DNN-based model as described in the next subsection.

B. DNN-based AUD

The detection of the received preamble sequences at the BS can be modelled as a multi-label classification problem, since multiple classes (i.e., preamble sequences) can be detected in received signal. We design a single neural network to accomplish this task of multi-label classification. The proposed DNN-based receiver architecture for AUD is illustrated in Fig 2. It replaces the "correlator" block of the conventional scheme shown in Fig 1. The input to the network is the output of the "pre-processing" block of Fig 1. This corresponds to the L-length frequency domain complex signal vector (denoted by S) obtained after CP removal, FFT and extraction of the sub-carriers on which preamble sequences are transmitted. Since neural networks cannot process complex numbers directly, we form a real vector of length $2L$ by stacking the real and the imaginary parts of S. Therefore, the input layer of the neural network will have $2L$ neurons and output layer will have N neurons. The loss function considered here is the binary cross entropy (BCE), which is given as,

$$\mathrm{Loss}_{\mathrm{BCE}} = -\frac{1}{N}\sum_{i=1}^{N} p_i \log(o_i) + (1-p_i)\log(1-o_i) \tag{6}$$

Where $p_i \in \{0,1\}$ is true indicator and $o_i \in [0,1]$ represents the predicted probability for i^{th} preamble.

1) Training: The proposed model was implemented using Tensorflow in Google Colaboratory, which learns the complex non-linear mapping through back propagation using a synthetically generated dataset. A large dataset ($\approx 8.5\times10^{5}$ data samples) was generated in MATLAB considering all possible combinations of preamble sequences and all possible values of timing and frequency offsets. The maximum number of users per TO, denoted by K, is chosen such that $\mathbb{P}(k \leq K) \geq 0.99$, i.e., we do not consider the values of k which occur for $\leq 1\%$ of the time. Note that the training dataset was generated considering a single tap Rayleigh fading channel, i.e., $h \sim \mathcal{CN}(0,1)$ for a particular value of the per-user signal-to-noise ratio (SNR), which was chosen to be 6 dB. The value represents the SNR at which NPRACH detection performance is evaluated for coverage area (CVA) 2 in NB-IoT[2]. Other details about the DNN training parameters are summarized in Fig 2.

2) Finding the threshold: The threshold can be optimized in order to meet different design criteria, e.g. minimize a specific type of error (false alarm or miss detection) or a metric which combines these two types of errors with different weights. The DNN was fed with the data corresponding to k active users and average of the output values produced by DNN was computed for all possible values of k. By analyzing the average output values, a threshold value ensuring that the false alarm probability was $\leq 0.1\%$ for any k was chosen. Again this number (0.1%) comes from the NPRACH detection performance metrics in NB-IoT [17].

3) Testing: In testing phase, the trained DNN is fed with the real vector of length $2L$ to produce an output vector

[2]NB-IoT has defined 3 coverage areas to support UEs in different regions of coverage, denoted as CVA 1, 2 and 3 along with their associated target SNRs and repetitions [17]

TABLE I
SIMULATION PARAMETERS

Bandwidth, B	180 KHz
Subcarrier spacing, Δf	3.75 KHz
Number of subcarriers, N_{SC}	48
N_{FFT} and N_{CP}	512 and 32 samples
Sampling frequency	1.92 MHz
Antenna configuration	1 Tx; 2 Rx
Channel model	EPA 1 Hz
Timing offset	rand(0, N_{CP}) samples
Frequency offset	rand(-200, 200) Hz
Number of TOs, T	40
Preamble length, L	47
Average number of users, λ	18

$O = [o_1, \ldots, o_{\mathrm{N}}]$, where $o_i \in [0,1]$ represents the probability of i^{th} preamble sequence being present in the received signal. Note that in the conventional method, multi-antenna again is exploited by combining the correlation energy from the two antennas, i.e., c_1 and c_2 are summed to get resultant output c as shown in Fig 1. Therefore, we exploit the multi-antenna gain for improved performance by running the proposed DNN model on each antenna and averaging their output vectors. Finally, we introduce the threshold obtained as explained in the previous part on the averaged output vector, which results in the activity indicator vector $\mathrm{A} = [a_1, \ldots, a_{\mathrm{N}}]$, where $a_{\mathrm{i}} \in \{0,1\}$ indicates the presence of the i^{th} preamble in the received signal. Although the training happened at a single SNR, the dataset considered for testing (with $\approx 23 \times 10^5$ samples) spanned different SNRs ranging from 0 dB to 20 dB in steps of 2 dB over an Extended pedestrian A (EPA) channel.

4) Timing offset estimation: In order to estimate the timing offset of the detected users, we use the conventional correlation based method itself. However, unlike the conventional case where we perform correlations over the entire set of N preambles, we now do so for only a subset of preambles (corresponding to the K detected preambles). This will reduce the computational complexity (as will be shown in Section IV-D).

IV. SIMULATION RESULTS AND DISCUSSION

In this section, we analyze the performance of the proposed DNN-based AUD scheme through simulations and compare it with the conventional correlation based AUD method.

A. Compatibility with 3GPP NB-IoT and mMTC

In accordance with the minimum number of OFDM symbols used for NPRACH transmission in NB-IoT, we consider the number TOs (T) to be 40 with each TO spanning one OFDM symbol. The length of the preamble sequences, L, is set to 47, since it is the largest prime-length ZC sequence that fits in one OFDM symbol consisting of 48 sub-carriers. The model is trained and tested with the maximum possible number of preambles per TO, i.e., $N = L - 1 = 46$. Further, the mMTC scenario suggested by 3GPP in [18] spans a cell area of 0.86 km^2 cell area with a device density of 10^6 devices per km^2 considering users transmitting every two hours. This results in 120 transmissions per second. Assuming that the GF resources are available every 150 ms, we can have 18 active users on average in each GF access attempt. Choosing $T = 40$ and $N = 46$ results in a total number of preambles $NT = 1840$, which is greater than $N_p = 1538$ required to serve $\lambda = 18$ users with an average all-user success (no collision) probability ($\mathbb{E}[p_{\mathrm{all}}]$) of 0.9 (obtained using Eqn. (4)). Further details about the simulation parameters are summarized in Table I.

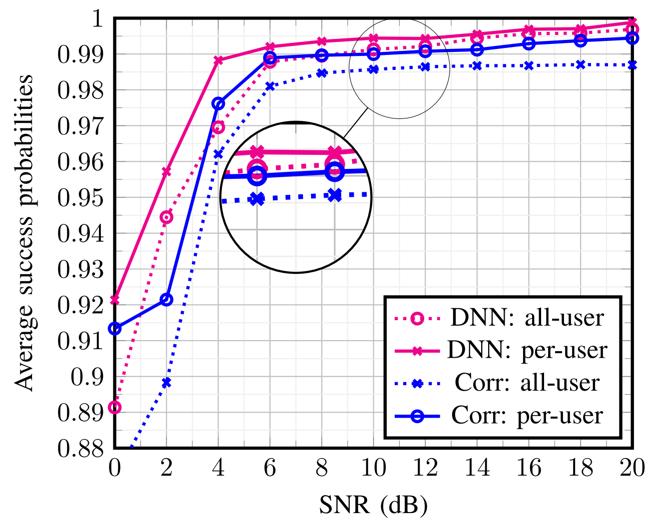


Fig. 3. Comparison of performances of conventional (correlation based) and DNN based AUD in terms of all-user and per-user success probabilities. Additionally (not shown in figure), it was observed that for SNR $\geq$ 6 dB, the false alarm probabilities were much below 0.1% and the error in timing offset estimation was within 7 samples (=3.645 μs) for both the conventional and the proposed methods.

B. Results

The performance metrics considered in this work are the all-user and per-user success probabilities. Since number of active users in any TO is random, we consider the average values of the performance measures. Particularly, given that $k \in [1, \ldots, K]$ active users are present with probability $\mathrm{p}(k)$, the all-user success probability is defined as the average probability of all k users being detected correctly. Similarly per-user success probability is defined as the average probability of a successful detection of an individual user. In our setting with $T = 40$ and $\lambda = 18$, using Eqn. (5), it can evaluated that $\mathbb{P}(k \leq 2) \geq 0.99$. Hence we set $K = 2$.

Fig. 3 demonstrates the AUD results obtained for the aforementioned performance metrics using the proposed DNN-based AUD architecture and the conventional method when users adopt the GF-NOMA procedure described in Section III-A. It is evident that the proposed method is comparable (or slightly better) than the conventional method in terms of both all-user and per-user success probabilities.

C. Comparison with NPRACH performance in NB-IoT

As per [17], the NPRACH detection performance in an EPA 1 Hz channel model requires a probability of detection $\geq 99\%$ (with false alarm probability $\leq$ 0.1% and error in timing offset estimation $\leq 3.645\mu$s) at 6 dB SNR for CVA 2 and approximately 12 dB SNR for CVA 1. From Fig 3, it can be seen that the proposed method for GF-NOMA easily meets the

NPRACH detection performance requirements. Moreover, the access method in NPRACH is an orthogonal multiple access (OMA) mechanism requiring users to randomly pick one of the 48 subcarriers. Therefore from Eqn. (3), it can be evaluated the on an average, only three users can be served with an all-user success (no collision) probability ≥ 0.9. However, using the proposed GF-NOMA scheme and the associated DNN-based AUD, we can serve $\lambda = 18$ users. Moreover, NPRACH uses 40 OFDM symbols (same as TOs in our case since 1 TO = 1 OFDM symbol) for CVA 1 and 160 OFDM symbols for CVA 2, whereas our proposed scheme can support both CVA 1 and CVA 2 using 40 OFDM symbols itself, which reduces the number of pre-configured resources required.

D. Computational Complexity

For the analysis of computational complexity, we will compare the two methods based on the number of real floating point operations required. In case of the conventional method, both preamble detection and timing offset estimation use correlated signal in the time domain as the input. Each correlation step involves multiplying the received signal with a preamble sequence in frequency domain which requires $6L$ real operations ($4L$ real multiplications and $2L$ real additions). This step is followed by the IFFT operation on the resulting signal, which takes approximately $\frac{34}{9} \times N_{\text{FFT}} \log_2(N_{\text{FFT}})$ real operations [19]. This entire procedure will be repeated for each preamble sequence (i.e., N times) and thus the total computational complexity of conventional method will be $\approx N \times (6L + \frac{34}{9} \times N_{\text{FFT}} \log_2(N_{\text{FFT}}))$. In case of proposed method, the received signal is directly fed to DNN without any correlation. Once the preambles are detected, we use the conventional method itself to estimate the timing offset, albeit only for the detected preambles. From the architecture given in Fig. 2, we get the complexity of DNN to be $\approx 32L^2 + 4LN$, considering that the complexity of a matrix-vector multiplication is $\approx 2N_1N_2$, where the matrix is of size $N_1 \times N_2$. Given that there are K active users, the total computational complexity of the proposed method will be $\approx 32L^2 + 4LN + K \times (6L + \frac{34}{9} \times N_{\text{FFT}} \log_2(N_{\text{FFT}}))$. Here $K << N$, since the active users are spread out across the TOs. By substituting our simulation parameter values where $K = 2$ and $N = 46$, we observe that the computational complexity of the proposed DNN-based AUD method is ≈ 7 times smaller than that of the conventional correlation based method.

V. Conclusion

In this paper, we proposed a grant free NOMA scheme compatible with the current NB-IoT physical layer along with a DNN-based architecture for active user detection (AUD). We demonstrated that the proposed DNN-based AUD has the following advantages - (i) it works well in in the presence timing and frequency offsets, which are inevitable in practical scenarios, (ii) its performance is comparable or better than the conventional correlation based AUD scheme for flat-fading (and low mobility) channels and (iii) its complexity is much smaller than the conventional detection scheme. The solutions proposed in this work are applicable for coverage areas 1 and 2 of NB-IoT and the AUD performance has been evaluated for scenarios involving no collisions. Extending the solutions to coverage area 3 and designing a unified architecture incorporating collision detection along with AUD forms the future work.

Acknowledgements

The authors would like to thank Science and Engineering Research Board (SERB) of India for the SERB-IMPRINT.IIC grant on the project "A Unified Broadband and Internet of Things (IoT) Base-station with Energy Efficient Resource Allocation and Caching Capabilities".

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