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Bi-Directional LSTM-Assisted Active User Detection for Uplink Grant-Free Code-Domain NOMA

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***Abstract*— GF-NOMA is a good access technology for massive IoT networks because many devices transmit their data without any request or permission, and the base station does not know the active users in the system. Instead, it receives a signal from multiple active users, so it must first identify the active users and then recover the symbols transmitted by the users from the mixed signal it receives. To identify the active users, a bidirectional LSTM network is used, considering the patterns of active users in multiple time slots. The input to this network is provided by the features of the signal, calculated by using the correlation operation. Once the active users are identified, the symbols transmitted by the users are estimated using the minimum mean square error method. This method provides better results in terms of the detection probability and bit error rate compared to the traditional method using the LSTM network.**

Keywords— Grant-Free NOMA, Active User Detection, Bidirectional LSTM, MMSE Detection, Sparse Uplink Access, Frequency-Selective Fading.

I. INTRODUCTION

The number of IoT devices in the wireless network has increased over the years. In many IoT applications, there are many devices registered in the system, but only a small number are transmitting at any time. Conventional orthogonal multiple access (OMA) schemes assign separate resources to each user. This is not efficient in the use of the spectrum because not many devices are always transmitting at any time. Non-orthogonal multiple access (NOMA) has been investigated as an alternative where many users are assigned the same resources. This makes the spectrum more efficient in use [1], [2]. Grant-free transmission is also useful for IoT systems because devices can transmit data directly without waiting for scheduling from the base station, which reduces delay and signalling overhead [3], [6]. However, in such systems the base station must first identify which users are active before detecting their transmitted signals.

Earlier approaches used compressed sensing and sparse recovery methods to detect active users by exploiting the sparse nature of IoT traffic [4], [5]. Recently, deep learning methods have also been explored for wireless signal detection [7][10]. In many IoT scenarios, once a device becomes active it may continue transmitting for a few time slots. Recurrent networks such as LSTM and BiLSTM can capture this type of temporal behaviour [11], [12]. In this work, we study multi-user detection in an uplink grant-free code-domain NOMA system using a BiLSTM-based model for active user detection, followed by MMSE estimation for symbol recovery. The system is evaluated under a frequency-selective Rayleigh fading channel for different user activity levels.

II. SYSTEM MODEL

We consider an uplink grant-free code-domain NOMA system consisting of K = 60 potential users. Transmission is organized into frames of J = 8 consecutive time slots. In each time slot, only a subset of users is active, and the base station does not have prior knowledge of the active set. To evaluate performance under different loading conditions, three average activity levels are considered:

$$S_{\text{avg}} \in \{8,30,40\}$$

Table 1: List Of Symbols And Notations Used In The Proposed Gf-Noma System

Symbol	Meaning
K	Total number of potential users present in the system
N	Length of the spreading sequence assigned to each user
J	Total number of time slots in one transmission frame
S_{avg}	Average count of users that are active
η	Parameter representing temporal activity correlation

L	Number of channel taps used in the multipath model
$x_{t,k}$	8-PSK symbol transmitted by user k at time t
s_k	Spreading sequence allocated to user k
$u_{t,k}$	Spread transmitted signal of user k
$A_{t,k}$	User activity indicator (1 = active, 0 = inactive)
$h_{t,k,l}$	Channel coefficient of the l-*th* multipath tap
y_t	Received signal vector at the base station
n_t	Additive noise component
σ^2	Variance of the noise
$z_{t,k}$	Output obtained from correlation operation
$f_{t,k}$	Feature vector provided as neural network input
H_t	Channel matrix corresponding to detected active users
$\hat{x}_t$	Estimated transmitted symbol vector
P_d	Probability of correct user activity detection
BER	Bit Error Rate

A. Signal Model

Each active user transmits symbols drawn from an 8-PSK constellation. The transmitted symbol of user k in time slot t is given by:

$$x_{t,k} = e^{j\frac{2\pi m}{8}}, \; m \in \{0,1,\dots,7\}$$

Each symbol carries $\log_2(8) = 3$ bits. Each user is assigned a spreading sequence of length $N = 120$. The spreading sequence of user k, denoted by $\mathbf{s}_k \in \mathbb{C}^N$, is generated from an independent and identically distributed complex Gaussian distribution,

$$s_k \sim \mathcal{CN}(0,1)$$

and then normalized to unit norm as $s_k \leftarrow \frac{s_k}{|s_k|}$

After spreading, the transmitted signal of user k in slot t becomes $u_{t,k} = x_{t,k} s_k$

Multiple active users transmit simultaneously over the same resource block.

B. User Activity Model

User activity evolves across time according to a first-order Markov process. Let $A_{t,k} \in \{0,1\}$ denote the activity state of user k in time slot t. At $t = 0$, exactly S_{avg} users are randomly selected as active. For $t \geq 1$, the state transitions are defined as

$$P(A_{t,k} = 1 \mid A_{t-1,k} = 1) = \eta,$$
$$P(A_{t,k} = 1 \mid A_{t-1,k} = 0) = \frac{S_{\text{avg}}}{K}(1-\eta),$$

where $\eta = 0.9$ represents the temporal persistence factor. This formulation maintains the expected number of active users close to S_{avg} while introducing correlation between consecutive time slots.

C. Channel Model

A frequency-selective Rayleigh fading channel with $L = 4$ taps is considered. The channel impulse response of user k in time slot t is defined as

$$h_{t,k} = [h_{t,k,0}, h_{t,k,1}, \dots, h_{t,k,L-1}]$$

where each tap follows

$$h_{t,k,l} \sim \mathcal{CN}\left(0, \frac{1}{L}\right)$$

The channel is assumed to experience slot-level fast fading, meaning the impulse response $\mathbf{h}_{t,k}$ varies independently from one time slot to the next. The effective channel vector is obtained through convolution of the spreading sequence and the channel impulse response: $g_{t,k} = s_k * h_{t,k}$, which has length $N + L - 1$.

Additive white Gaussian noise is added at the receiver: $n_t \sim \mathcal{CN}(0, \sigma^2 I)$, where the noise variance is determined by the signal-to-noise ratio (SNR),

$$\sigma^2 = \frac{1}{\text{SNR}_{\text{lin}}}$$

The SNR range considered in the simulation is from 0 dB to 20 dB in steps of 4 dB.

D. Received Signal Model

In each time slot t, the received signal is expressed as :

$$y_t = \sum_{k=1}^{K} A_{t,k}\, x_{t,k}\, g_{t,k} + n_t$$

The base station observes $\mathbf{y}_t$ without knowledge of the activity matrix $\{A_{t,k}\}$ and must perform active user detection followed by symbol estimation. Performance is evaluated using Monte Carlo simulation with 250 independent realizations per SNR point.

III. PROPOSED DETECTION FRAMEWORK

To perform multi-user detection in the considered grant-free system, a two-stage framework is adopted. First, a Bidirectional Long Short-Term Memory (BiLSTM) network is used to identify active users across multiple time slots. Then, Minimum Mean Square Error (MMSE) estimation is applied only to the detected active users for symbol recovery.

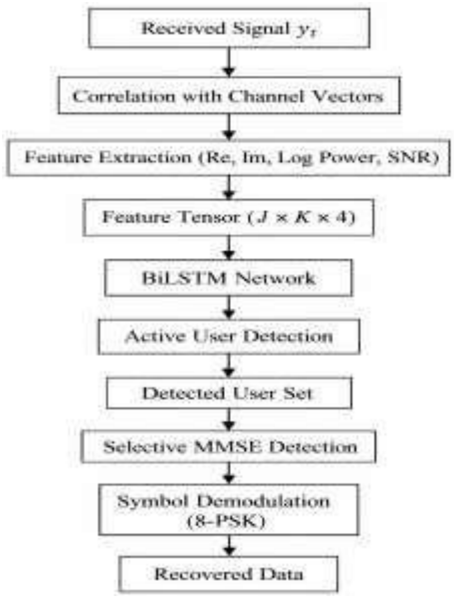

Fig. 1. Proposed BiLSTM-MMSE multi user detection framework

A. Feature Extraction

For each time slot t, the received signal $\mathbf{y}_t$ is correlated with the effective channel vector $\mathbf{g}_{t,k}$ of each user. The correlation value is computed as $z_{t,k} = g_{t,k}^H y_t$.

where $(\cdot)^H$ denotes the conjugate transpose.

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From each complex correlation value $z_{t,k}$, a four-dimensional feature vector is constructed:

$$f_{t,k} = [\mathrm{R}(z_{t,k}),\ \mathrm{I}(z_{t,k}),\ \log_{10}(|z_{t,k}|^2 + \epsilon),\ \frac{\mathrm{SNR}_{\mathrm{dB}}}{20}]$$

where ϵ is a small constant to ensure numerical stability.
The features are computed for all $K = 60$ users across $J = 8$ time slots, forming an input tensor of dimension $(J, K, 4)$. For each time slot, feature normalization is performed using the mean and standard deviation of that slot before being provided to the neural network.

B. BiLSTM-Based Active User Detection

The feature tensor of size $(J, K, 4)$ is provided as input to the neural network. A permutation operation is first applied so that each user's temporal sequence is processed independently. For each user, the sequence of length $J = 8$ is passed through a Bidirectional LSTM layer with 96 hidden units in each direction and with return sequences enabled. The BiLSTM output is then processed by:

- Batch normalization,
- A time-distributed fully connected layer with 48 neurons and ReLU activation,
- A final time-distributed dense layer producing one logit per user per slot.

Binary cross-entropy loss with logits is used for training. The network is trained using:

- 6000 generated training samples,
- Batch size of 64,
- 15 training epochs,
- Adam optimizer with learning rate 0.0005.

The logits are converted to probabilities using a sigmoid function. A user is declared active in slot t if the predicted probability exceeds 0.5.

C. Selective MMSE Data Detection

After identifying the active users in each time slot, MMSE detection is applied only to the detected subset. Let S_t denote the set of detected active users in slot t. The reduced channel matrix $\mathbf{H}_t$ is formed using only the effective channel vectors corresponding to users in S_t. The MMSE estimate of the transmitted symbol vector is computed as $\hat{x}_t = (H_t^H H_t + \sigma^2 I)^{-1} H_t^H y_t$.
The estimated symbols are then demodulated using 8-PSK decision rules. The bit error rate (BER) is computed by accounting for correctly detected users, missed active users, and false detections. By restricting MMSE estimation to the detected users rather than all $K = 60$ users, computational complexity is reduced, particularly under sparse activity conditions.

IV. SIMULATION SETUP

This section explains how the system was tested and what parameters were used in the implementation.

A. System Parameters

The total number of users considered in the system is $K = 60$. Each transmission frame contains $J = 8$ time slots. A spreading length of $N = 120$ is used for each user. The wireless channel is modeled as a frequency-selective Rayleigh fading channel with $L = 4$ taps. The activity persistence parameter in the Markov model is fixed at $\eta = 0.9$. The key parameters used in generating the training dataset are summarized in Table 2.

Table 2: Simulation Parameters Used In The Proposed Gf-Noma System

Parameter	**Value / Setting**
Modulation scheme	8-PSK
Total number of users K	60
Spreading sequence length N	120
Number of time slots J	8
Average active users S_{avg}	{8, 30, 40}
Channel model	Frequency-selective Rayleigh fading ($L = 4$)
User activity model	First-order Markov process
Temporal correlation η	0.9
SNR range	0 – 20 dB
Monte-Carlo simulations	250 runs
BiLSTM hidden units	96
Dense layer neurons	48
Training dataset size	6000 sequences
Batch size	64
Training epochs	15
Optimizer	Adam
Learning rate	0.0005

To check how the detector performs under different traffic conditions, three average active user levels are tested: $S_{\mathrm{avg}} \in \{8,30,40\}$.
These represent low, medium, and high system load cases. The SNR is varied from 0 dB to 20 dB in steps of 4 dB. For each SNR value, 250 independent Monte Carlo runs are performed and the results are averaged. All users transmit 8-PSK symbols, which correspond to 3 bits per symbol.

B. Training Setup

The neural network models are trained using synthetic data generated from the system model. In the implementation, 6000 training samples are generated. Both the proposed BiLSTM model and the LSTM baseline use the same training configuration to ensure a fair comparison.
The training details are :

- 6000 generated samples
- Batch size of 64
- 15 epochs
- Adam optimizer with learning rate 0.0005
- Binary cross-entropy loss (with logits)

During training, the average number of active users is fixed at 8. After training, the same trained model is evaluated under all three activity levels (8, 30, and 40) without retraining.

C. Reference Methods

To compare performance, two additional methods are evaluated:

1. Oracle MMSE : In this case, the receiver is assumed to know the true active users. MMSE detection is applied only to those users. This gives the best possible performance under perfect activity knowledge.
2. LSTM-CS : A unidirectional LSTM-based detector with the same number of hidden units and dense layer size as the proposed model. The only difference is that it does not use bidirectional processing.

The proposed method combines BiLSTM-based activity detection with selective MMSE symbol estimation.

D. Performance Metrics

Two metrics are used to evaluate performance.
The first metric is the probability of detection:

$$P_d = \frac{\text{Number of correctly detected active users}}{\text{Total number of true active users}}$$

The second metric is the bit error rate (BER):

$$\text{BER} = \frac{\text{Total number of bit errors}}{\text{Total number of transmitted bits}}$$

V. RESULTS AND DISCUSSION

In this section, the performance of the proposed BiLSTM-MMSE based multi-user detection framework is evaluated. The results are compared with the LSTM-CS baseline and the Oracle MMSE detector. The Oracle detector assumes perfect knowledge of the active user set and therefore represents the ideal upper bound. The system performance is evaluated for three different activity levels: 8, 30, and 40 active users. The evaluation is performed using probability of detection (Pd) and bit error rate (BER) across an SNR range from 0dB to 20dB.

A. Detection Performance of Proposed Model

The detection capability of the proposed model under different user activity levels is shown in Fig 2. The figure illustrates the probability of detection as a function of SNR for 8, 30, and 40 active users. From the figure, it can be observed that the detection probability increases steadily as the SNR increases. For the case of 8 active users, the detection probability improves from approximately 0.29 at 0 dB to about 0.93 at 20 dB. When the number of active users increases to 30 and 40, the detection performance slightly decreases due to stronger multi-user interference. However, even under heavy loading conditions, the proposed model maintains reliable detection performance. This indicates that the BiLSTM network is capable of learning temporal activity patterns effectively.

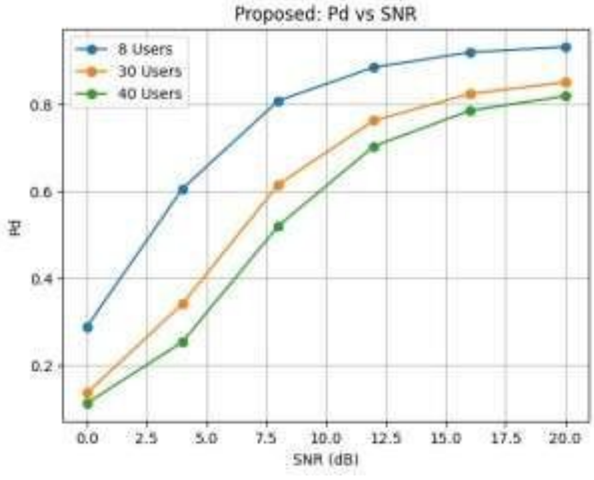

Fig. 2. Detection Performance of Proposed Model

B. BER Performance of Proposed Model

Fig 3 shows the BER performance of the proposed model with different numbers of active users. It is observed that the BER decreases as the SNR increases. When there are 8 active users, the BER decreases from 0.88 to 0.10 as the SNR increases from 0 dB to 20 dB. However, when there are 30 or 40 active users, the BER is higher because there is interference. But the trend is the same: the higher the SNR, the easier it is to detect the symbol.

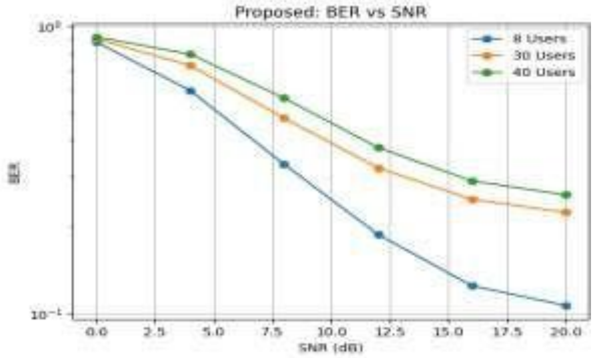

Fig. 3. BER Performance of Proposed Model

C. Detection Performance Comparison (30 Users)

To assess how well the proposed model is performing, we compare it with the performance of the LSTM-CS model and the Oracle MMSE detector. In Figure 4, we present the results of the detection probability for 30 active users. The Oracle model is performing perfectly since it has the exact knowledge of the active users. The performance of the LSTM-CS model is better compared to the traditional methods but still worse compared to the proposed model. The proposed BiLSTM model reaches a 0.85 detection probability at 20 dB, whereas the LSTM-CS model is at 0.74. The major contribution of the proposed model is the ability of the BiLSTM model to learn in both forward and backward directions.

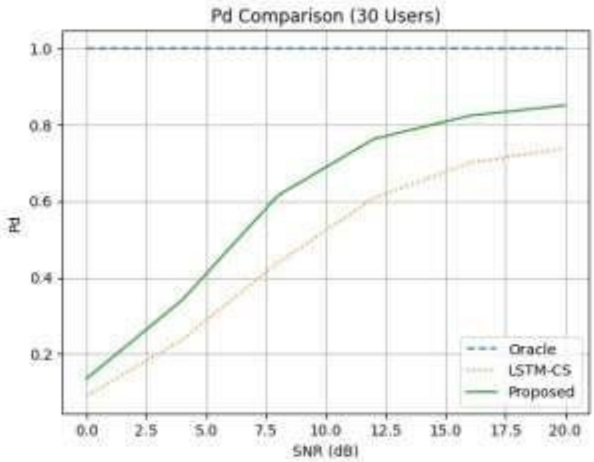

Fig. 4. Detection Performance Comparison (30 Users)

D. BER Comparison (30 Users)

It can be observed from Figure 5 that the proposed method has a lower BER compared to the LSTM-CS method at all values of SNR. At an SNR value of 20 dB, the proposed method has a BER value of about 0.22, while the BER value using the LSTM-CS method is about 0.35.

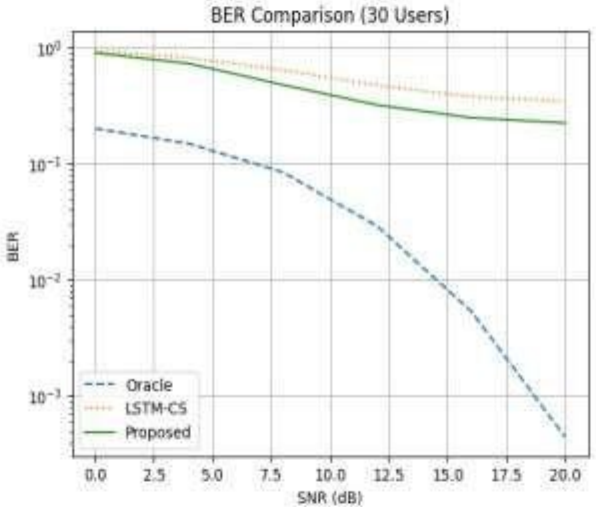

Fig. 5. BER Comparison (30 Users)

E. Detection Performance Comparison (40 Users)

Figure 6 presents the detection performance when there are 40 active users. This is a busy system with high interference from many users. However, the performance of the proposed detector based on the BiLSTM model is better than the LSTM-CS model. Under a 20 dB scenario, the detection probability using the proposed method is 0.82, whereas the detection probability using the LSTM-
-CS model is 0.70.

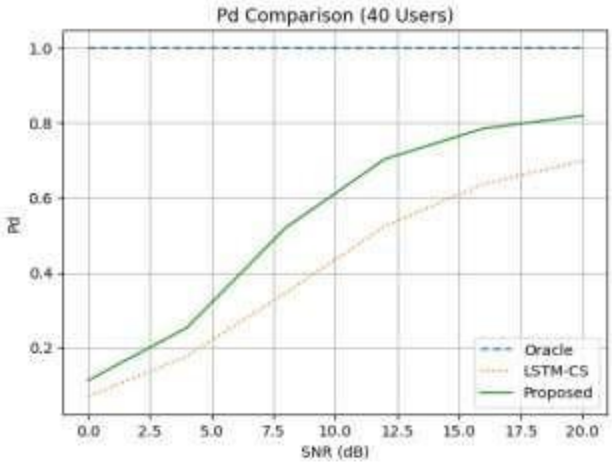

Fig. 6. Detection Performance Comparison (40 Users)

F. BER Comparison (40 Users)

Figure 7 shows a comparison of BER for 40 active users. As expected, BER is higher than in sparse activity because more interference is involved. However, it can be seen that the proposed model outperforms the LSTM-CS model. At 20 dB, the BER for the proposed model is about 0.26, while for LSTM-CS it is about 0.39.

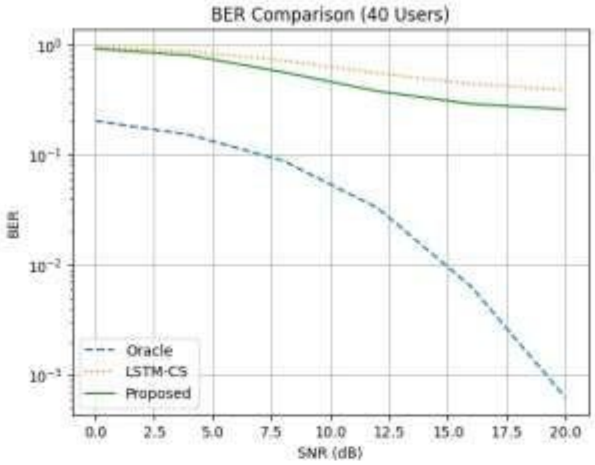

Fig. 7. BER Comparison (40 Users)

VI. CONCLUSION

In this paper, a BiLSTM-based approach is used for active users' detection in an uplink grant-free NOMA scheme. The model learns the active users over a number of time slots and detects them. Once detected, MMSE is used for symbol recovery from the active users. Simulation results show that the model outperforms the baseline in terms of detection probability and BER for different values of active users. In addition, it can be seen from the results that the higher the SNR, the better the performance.Overall, the proposed approach improves multi-user detection performance by using temporal information in user activity. In future work, other deep learning architectures can be explored to further improve detection accuracy.

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