

Efficient Power-Division NOMA for Intelligent Optical Access Network Enabled by Deep Learning

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Abstract: We propose and experimentally demonstrate both synchronized downlink and asynchronous uplink NOMA using deep learning techniques, providing expansibility for an ultra-dense network and enabling low-cost intelligent optical access network.

1. Introduction

The explosive growth in new applications such as virtual reality, super-high resolution video, and interactive multimedia services have been generating tremendous data traffic, which requires strict demand on bandwidth, data rate and scalability in optical access network (OAN). Currently, the widely used time-division multiplexing (TDM) and wavelength division multiplexing (WDM) in OAN cannot fulfill the low-cost flexible deployment to sustain the exponentially growth of users. To address these challenges, non-orthogonal multiple access (NOMA) technologies were introduced, which aims to increase the network throughput and serve massive network subscribers [1]. In this paper, we focus on power-domain NOMA, dubbed as PD-NOMA. Through adapting to multi-users' path loss, we can deliver multi-user services simultaneously using different power ratios. Since all the transmitting signals to optical network unit (ONU) are generated in the centralized optical line terminal (OLT), synchronized PD-NOMA can be utilized in the downlink. However, due to the cost and latency from ranging the uplink signals, asynchronous PD-NOMA becomes a preferred solution in the uplink. To retrieve the information for each user with different signal-to-interference-plus-noise ratio (SINR), successive interference cancellation (SIC) decoder is utilized [1]. However, error propagation from the symbol/waveform subtraction may degrade the performance of some users. Besides, severe security concerns are raised since the users with more SIC layers need to decode the information for other users which may cause leakage of sensitive data. Moreover, the SIC decoder needs cumbersome waveform reconstructions and subtractions in the uplink PD-NOMA, which adds extra latency to low SINR users [2]. Deep neural network (DNN) has attracted tremendous interests to be applied into various pain-killing use cases with its superior modeling capacity. Besides, recent developments in hardware and DNN training algorithm make DNN more feasible to be implemented in OAN [3]. Training the DNN is time and resource consuming. However, once the initial training is completed, the querying just involves some matrix multiplications, the querying complexity only grows linearly with the number of hidden layers while the modeling capacity enhances exponentially [4]. In practical scenarios, the OAN link condition is dynamic due to aging and temperature variations, while still can be solved by transfer learning [5]. In this paper, for the first time we propose and demonstrate a DNN decoder enabled NOMA supporting both synchronized downlink and asynchronous uplink. A 10-Gb/s per user transmission is achieved, allowing a more secure and scalable OAN.

2. Experimental Setup and Results

Fig. 1(a) illustrates the architecture of the proposed NOMA OAN system/testbed. The prototype consists of the OLT and multiple ONUs. At the OLT side for the downlink NOMA, we multiplex the information to different ONUs in the symbol level. The power-ratio for different ONU is determined by the path loss to the ONU. A larger power-ratio is assigned to the ONU with a higher path loss. For the uplink NOMA, the power ratio is allocated based on to the OLT's received optical power (RoP) from each ONU. To fully utilize the path loss difference and maximize the sensitivity at OLT for the uplink, we typically assign a smaller power ratio to the ONU with a higher path loss in contrast to the downlink. In the synchronized downlink NOMA, we assign the same data rate for all the users. Without loss of generality, we conduct a proof-of-concept experiment for the synchronized downlink NOMA with 3 ONUs, dubbed as user#1, user#2, and user#3 according to the descending order of power-ratio. The transmitted power ratio associated with each user is [0/-7/-14]-dB. In the asynchronous uplink, we test the scenario of 2 users with 9-dB power difference. The ratio is chosen to ensure an enough signal-to-noise-ratio (SNR) for the lowest power user and to enable performance gradient among users with different sensitivity requirements. For both of the downlink and uplink, we utilize a DNN decoder to decode the signals for different users. Unlike the noise, the interference from other users have specific pattern which can be learned and eliminated by the DNN decoder directly. Besides, the DNN decoder can simultaneously mitigate the signal distortion and inter-symbol interference from the nonlinear and filtering effects [3]. Fig. 1(b) shows the structure of the DNN decoder, we take the input sample along with its 20 previous and 20 subsequent samples as the input layer. Besides, we have 5 hidden layers, the first two layers have 1024 neurons, while the remaining layers have 256 neurons. The number of neurons at the output layer is set to 8, such that the DNN decoder can support up to PAM-8 modulation for each user. ReLu activation function is applied

in each neuron to avoid the gradient vanishing. Also, we implement Dropout and Early Stopping mechanism to eliminate overfitting. The loss function is calculated based on the categorical cross-entropy, and we use Adamax algorithm to minimize the loss. We build a bi-directional OAN testbed to verify the system feasibility. With different bits sequence into the OAN, we map the bits into OOK symbol independently. And a single symbol stream is generated by combining the bits sequences using the predefined power-ratio. After the digital to analog conversion (DAC), the signal is boosted by a modulator driver and is converted to optical domain through an intensity modulator. In the downlink of the ONU, the optical signal is detected by a photodetector (PD) and digitized by an oscilloscope. The digitized samples are fed into the DNN for signal decoding, with 60 percent for training and 40 percent for testing. The percentage of the training subset can be much reduced in a larger dataset. In the uplink, the signals are generated at each ONU, which are combined and detected at the OLT. The OLT also uses the DNN decoder to decode the uplink signal from each ONU separately.

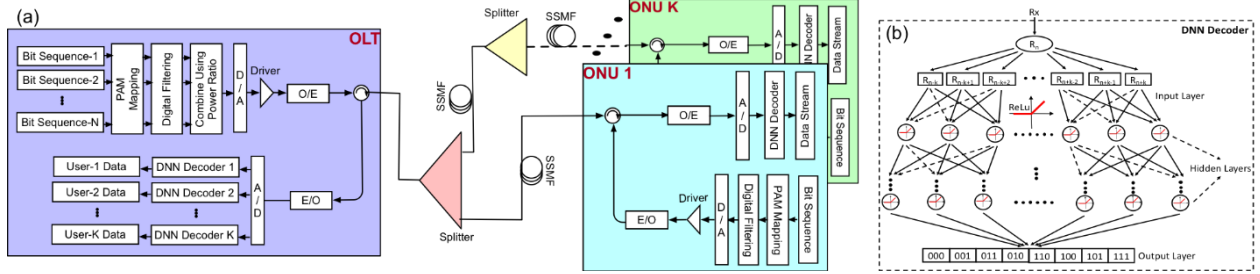


Fig. 1. (a) Experimental setup and architecture of the proposed NOMA OAN system, (b) DNN decoder structure.

The experimental results for synchronized downlink are shown in Fig.2(a). We measure the sensitivity for 3 ONUs at 10-Gb/s per user using the power-ratio allocation stated above. Noticeably, the sensitivity for each ONU is -11.8 dBm, -8.7 dBm and -4.1 dBm respectively, at 7% FEC threshold. The ONU's sensitivity depends on its power-ratio. Here, the sensitivity margin of user#2 over user#3 is 4.6 dB, while the margin between user#1 and user#2 is 3.1 dB. which means we can provide fair services to each ONU even with different path loss. We also scan the data rate for each ONU from 2 Gb/s to 10 Gb/s per user as shown in Fig.2(b). The lower data rates reach higher sensitivity, which provides the OAN with more flexibility to adapt various demands. The uplink transmission performance with 2-users are shown in Fig.2(c). The data rate is set to 10 Gb/s per user as well. The symbols from the two ONUs are fully asynchronous with half-symbol duration offset as the worst case scenario. The real performance should be beyond the worst case. For the user with higher power received at the OLT, the sensitivity is -12.6 dBm, while the other user is -7.5 dBm, with a 5.1-dB difference. Compared with the conventional SIC decoder, the DNN decoder is more intelligent in signal decoding. It doesn't need to perform constellation subtraction or the complex waveform subtraction. Besides, the order of PAM modulation for each user is transparent to the DNN decoder structure. The sensitivity of both the downlink and uplink transmission can also be significantly improved with avalanche photodetector (APD).

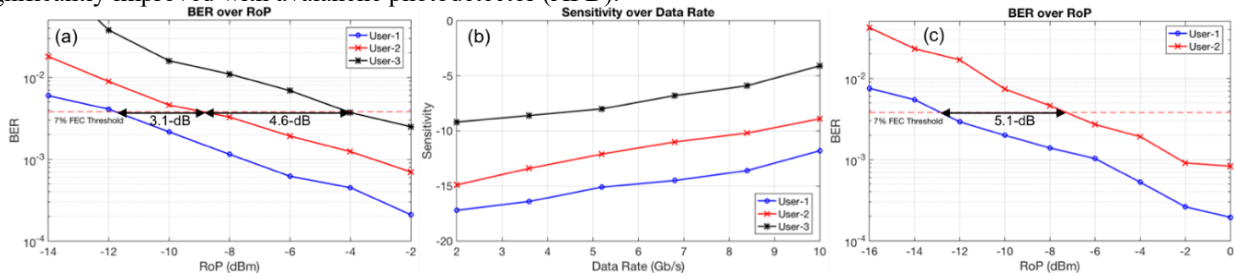


Fig. 2. (a) Synchronized downlink BER over RoP for each ONU, (b) downlink sensitivity over data rate for each ONU, (c) BER over RoP for 2 ONUs in the asynchronous uplink.

3. Conclusion

We propose and experimentally demonstrate a DNN decoder enabled PD-NOMA transmission for both synchronized downlink and asynchronous uplink with 10 Gb/s per user data rate. The proposed scheme provides the OAN with extra dimension of expansibility to support massive subscribers. The DNN decoder shows superiority over traditional SIC decoder from its higher security, better scalability and less complexity in decoding. With the rapid cost-reduction and performance boost in Deep Learning hardware, the DNN decoder will be more deployable in the OAN infrastructure.

References

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