Next-Generation Passive Optical Network Based on Sparse Code Multiple Access and Graph Neural Networks

Hui Yang, Xianzhuo Zhang, Bangjiang Lin, Pengcheng Deng, and Anlin Yi

***Abstract*—Sparse code multiple access (SCMA) is a promising technology to provide high throughput and overall improved system performance at affordable cost for next-generation passive optical networks (NG-PONs). Message passing algorithm (MPA) based on a factor graph is usually used for low-complexity multiuser detection in SCMA. However, MPA requires accurate and effective channel estimation due to the interference between the user's signals on the same resource block and suffers uncertain convergence caused by the cycles in the factor graph. In this paper, a graph neural networks (GNN)-based detection method is proposed for SCMA-PON, which performs channel impairment compensation and signal detection in a joint manner. 25.5 Gb/s SCMA-OFDM system over 20/60 km single mode fiber link is simulated to demonstrate the feasibility with 8.5-G class optical devices. The simulation results show that GNN-based detection method outperforms MPA and is more robust to the nonlinear distortion for the same level of computational complexity.**

***Index Terms*—Passive optical network, non-orthogonal multiple access, sparse code multiple access, graph neural network.**

I. Introduction

Vigorous development of Internet of things and the exponentially growth of traffic demand is pushing the optical access networks to provide larger capacity at affordable cost [1]. Long-reach passive optical networks (LR-PONs) have attracted much attentions from service providers and researchers in the evolution of optical-access networks, which can simplify the hierarchy of the overall network and save the cost further due to the eliminating of the electronic interface [2]. Furthermore, the quality of service for real-time traffic could be improved due to reduced number of hops [3]. Considering the applications, PONs based on Time Division Multiplexing (TDM) technology with reach extension have been defined in the standard by ITU-T for the next generation passive optical networks (NG-PONs) [4].

Manuscript received September 24, 2021; accepted November 12, 2021. Date of publication November 16, 2021; date of current version December 8, 2021. This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFB2201103, and in part by Sichuan Science and Technology Program, China under Grant 2020YFSY0021. *(Corresponding authors: Hui Yang and Bangjiang Lin.)*

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Digital Object Identifier 10.1109/JPHOT.2021.3128420

As the access speed evolves to 100 Gb/s beyond, conventional TDM-PON with pulse-shaped on-off-key (OOK) modulation meets with severe bottlenecks due to the limitations of chromatic dispersion, implementation of high-speed burst-mode transceivers and packet latency [5]. Novel architectures and methods for next-generation PONs with larger capacity, higher spectral efficiency and higher cost-effectiveness are required. Various multiplexing methods using orthogonal resources in either frequency (wavelength), state of polarization, code domain or space have been proposed to tackle the performance and cost challenges in LR-PON [6]–[9]. In these multiplexing dimensions, the orthogonality of signals must be guaranteed, otherwise different signals cannot be separated correctly without affecting the detection of other signals.

Non-orthogonal multiple access technology has attracted considerable attention over the past years. Sparse code multiple access (SCMA) is a promising non-orthogonal multiple-access technique, in which information bits are spread to non-orthogonal complex codewords in a sparse manner [10]. Through sparse spread spectrum in code domain and non-orthogonal superposition, SCMA can accommodate more users over the same number of resources, thus to improve the spectrum utilization and relieve the requirement for device bandwidth. Fundamental works on the codebook and decoding have been carried out to improve the reliability of SCMA-based systems [11]–[13]. In [14], a non-orthogonal optical multicarrier access system based on filter bank and SCMA was proposed and demonstrated with 60 km single mode fiber. Maximum a posteriori (MAP) detection is used to decode the received SCMA signal. However, it requires a significant number of operations with growth of the network size. Message Passing Algorithm (MPA) based on factor graph is proposed with lower complexity, which iteratively updates the status of function nodes and variable nodes until the probability of the user node converges [15]. Due to the inevitable existence of the loops, the iterative algorithm has uncertain convergence problem, thus to be inherently suboptimal [16]. In addition, MPA-based multiuser detection is performed after channel equalization. The channel state information (CSI) has an important impact on the performance of MPA, so accurate channel estimation methods are required to obtain perfect CSI.

In recent years, machine learning (including deep learning) technology has shown great success in the field of computer vision, speech recognition and natural language processing with

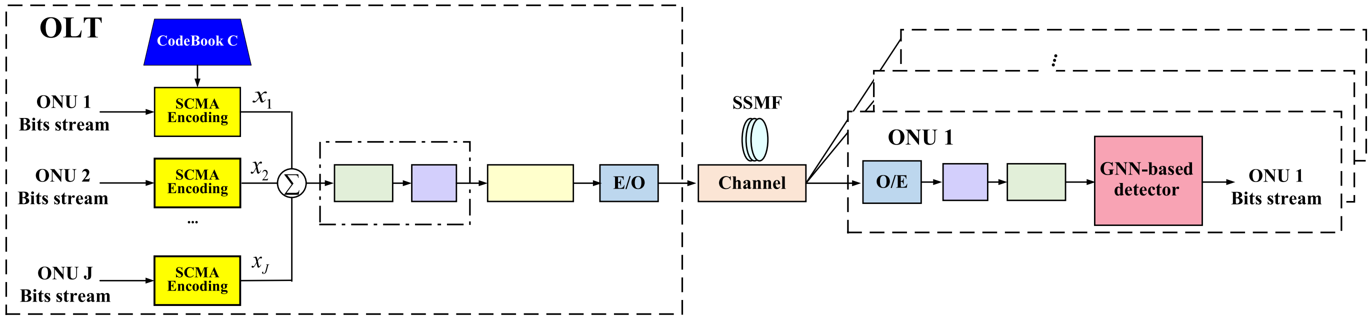

Fig. 1. NG-PON based on SCMA and GNN system model.

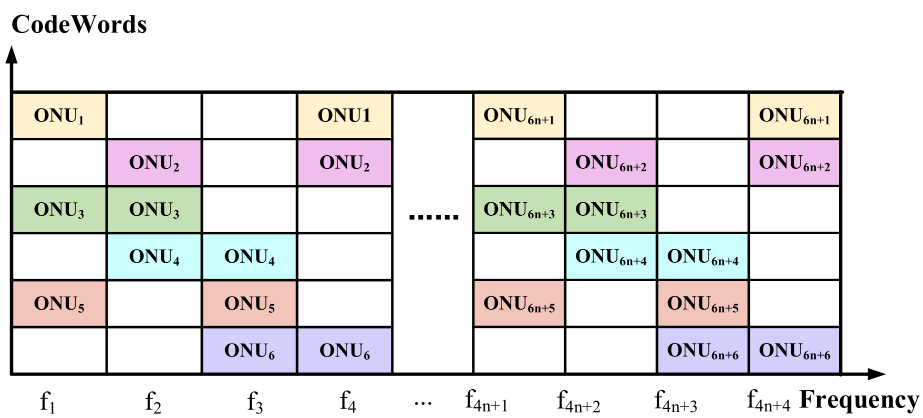

Fig. 2. SCMA-OFDM mapping with six users and four resource blocks.

its powerful cognitive abilities. In optical communications, machine learning has been considered as a powerful nonlinear decision classifier to decode the distorted signals by inverting the effects of linear and nonlinear distortions. Various machine learning methods are proposed to extract the features of Euclidean data and achieve great success [17]–[22]. Graph Neural Network (GNN), as a deep learning method that operates on graph domain, has been widely concerned and adopted in non-Euclidean data structures [23]–[26].

In this paper, to our best knowledge, we firstly propose a LR PON based on SCMA and GNN, in which channel impairment compensation and multi-user detection are conducted using GNN in a single shot. The complex nonlinear mapping between input and output space is formed without CSI to help to reverse the influence of nonlinear distortion in GNN. And it can learn to adjust the weights of the edges and to capture the dependence between the nodes via message passing, thus to realize multi-user detection. Simulations are demonstrated to confirm that LR SCMA-PONs based GNN provides better transmission performance and less computational complexity than that with MPA.

The rest of this paper is organized as follows. In Section II, we describe the principle in the system model. Section III introduces the simulation setup and the simulation results. Conclusions are provided in Section IV.

II. Principle

Fig. 1 illustrates the proposed NG-PON based on SCMA and GNN system model. Consider a LR PON with J users and K resource blocks ($K<J$). At the transmitter, each user is assigned with one codebook, which includes P non-zero positions with Q-dimension codewords ($Q<<P$). The independent bit stream of each user is firstly mapped the multi-dimensional codewords selected from the codebook in the SCMA encoding module. And then after physical resource element mapping, the codewords of different users are non-orthogonal superimposed on the same resource block. Here frequency domain resource block is adopted and orthogonal frequency division multiplexing (OFDM) technology is chosen to transmit SCMA signal. The superimposed information is modulated into K OFDM subcarriers through inverse discrete Fourier transform (IDFT). Fig. 2 shows the principle of SCMA-OFDM mapping, where six users and four resource blocks are adopted as an example. It can be seen that SCMA system can accommodate more users when occupying the same number of physical resources with sparse spread spectrum in code domain and non-orthogonal superposition. After the preambles for synchronization are added, the generated signal is converted into optical signal and transmitted through single mode fiber (SMF). It should be noted, in this paper, we focus on the SCMA and GNN-based PON scheme, and OFDM is chosen as the representation of various DSP methods for

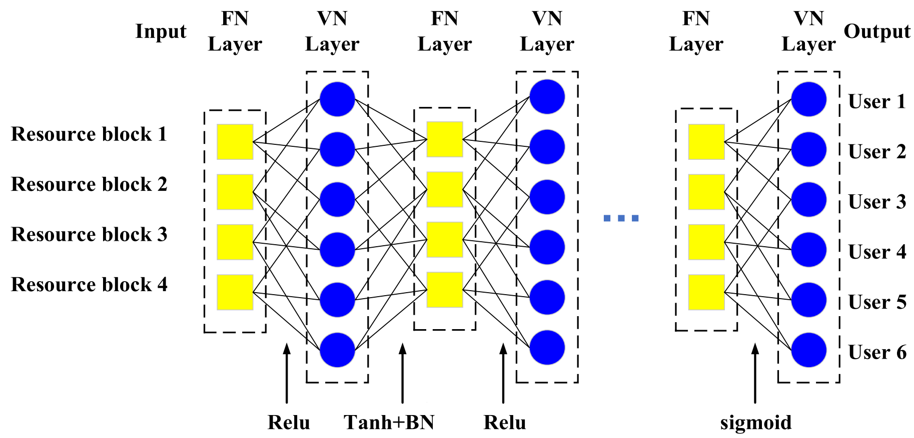

Fig. 3. GNN model proposed with six variable nodes and four function nodes.

transmission. It can improve the spectral efficiency and exhibits very high resilience to linear impairment [5]. However, as a multi-subcarrier modulation, OFDM has a high peak to average power ratio (PAPR), which requires high linearity for optical modules and electrical components. Deep learning based on neural network has been applied to the reduction of OFDM-based nonlinear distortion in power amplifiers by learning the nonlinear impairments from the observed data in contemporary wireless communications [27]. Single-carrier modulations, such as SCFDM, are preferred due to the lower PAPR. The proposed architecture can be easily extended to combine with other multiplexing technology and advanced DSP methods. After transmission link, the received signal is converted into electrical signal through a photodetector. The received signal can be expressed as

$$\boldsymbol{y} = \sum_{j=1}^{J} diag\left(\boldsymbol{h}_j\right)\boldsymbol{x}_j + \boldsymbol{z} \tag{1}$$

Where $y = [y_1, y_2, \ldots, y_K]$, $x_j = [x_{j,1}, x_{j,2}, \ldots, x_{j,k}]$ and $h_j = [h_{j,1}, h_{j,2}, \ldots h_{j,k}]$ represents the received, transmitted signals by the j-th ONU and the channel vector, respectively; z represents the noise vector. After frame synchronization, the OFDM signal are demodulated by removing CP and DFT operation. Then the SCMA signals are decoded directly using the GNN-based detector. For the traditional receiver, the multi-user detection problem usually be solved by using MAP or MPA with excessive search, which will estimate $\hat{x}_j$that maximize the posterior probability of codeword under the prior knowledge of received signal vector y and channel vector h_j, as shown in (2)

$$\hat{x}_j = \arg\max_{x_j \in [C]} P\left(x_j | y\right) \tag{2}$$

However, the performance of traditional multi-user detection algorithms largely depends on the accuracy of channel estimation, and the complexity increases sharply with the increase of the number of users. In the proposed scheme, GNN is a tool that learns the system impairments and the interaction between nodes from the observed data and builds a probabilistic model for multi-user detection without CSI.

In our specially designed GNN, factor graph is selected as the graph structure. Define factor graph by $G(N, E)$, N is the set of nodes including function nodes (FN) and variable nodes (VN) and E is the set of edge. The edge $e_{i,j} \in E$ connects a function node FN_i to a variable node VN_j. Fig. 3 shows the GNN model proposed with six variable nodes and four function nodes. The input signal is firstly divided into real and imaginary components. Then it is followed by FN and VN layers according to the type of nodes, which iteratively update the state information of nodes to spread information to the whole graph. In the initialization stage, the probability information of variable nodes is set to be equal. In the iteration process, the variable node is updated first as following:

$$I^t_{k\to j} = \sum_{j\in ne(i)} \mathrm{Relu}(w_{j,i} * I^{t-1}_{j\to k} + b_{j,i}) \tag{3}$$

$$\mathrm{Relu}(x) = \max(0, x) \tag{4}$$

the update of function nodes is given by

$$I^t_{j\to k} = \sum_{c\in\zeta_j/k} \mathrm{Tanh}(BN(w_{c,j} * I^t_{c\to j} + b_{c,j})) \tag{5}$$

$$\mathrm{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{6}$$

Here, Relu and Tanh are chosen as the activation function to introduce nonlinearity for the variable nodes and the function nodes, respectively. w indicates the filter parameters, which has a great impact on the learning ability of GNN. b denotes the bias vector. Moreover, batch normalization (BN) is adopted to prevent over fitting and improve the training speed. Following the last FN layers, the output is fed into the output layer (the last VN layer) with a sigmoid activation function, as shown in:

$$\mathrm{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

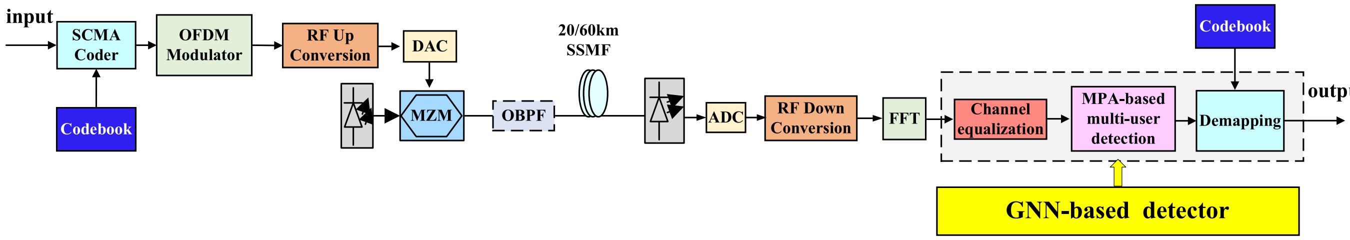

Fig. 4. The simulation setup of LR-PON based SCMA and GNN.

The output of sigmoid function is the 6∗2 probability matrix $\mathbf{Z}$ and fed into a hard decision module with a threshold value 0.5. If $\mathbf{Z}_{(i,j)} > 0.5$,the received j-th data bit of the i-th user is 1, otherwise it is 0. The loss function of the model is mean square error (MSE), expressed as follows:

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(z_j^{label} - z_j^{predict}\right)^2 \tag{8}$$

Where z_j^{label} denotes the original value corresponding to the j-th bit and $z_j^{predict}$ denotes the predicted value of the j-th bit. The loss function is back propagated to update the weight parameters with Adam optimizer.

III. Simulation Setup and Results

The transmission performance of the proposed LR PON based on SCMA and GNN is investigated with the commercial software MATLAB 2014a, VPItransmissionMaker 9.2, Python 3.6, TensorFlow 1.10 and Keras 2.1. The schematic diagram of simulation setup is shown in Fig. 4. At the OLT, the SCMA-OFDM signal is generated offline with digital signal processing. The input bit stream is generated randomly in MATLAB and encoded into SCMA symbols according to the codebooks proposed in [28]. Each codeword is labeled by 2-bit. Next, the SCMA signals are encoded into SCMA-OFDM signals with the sizes of IDFT and CP 256 and 8, respectively. Then, the baseband SCMA-OFDM signals are up-converted to a 17-GHz radio frequency (RF) carrier. The preamble is inserted at the beginning of SCMA-OFDM data frame synchronization and channel estimation, which consists of two 64-point Chu-sequences for frame synchronization and one 256-point Chu-sequence for channel estimation. A CW laser with the center wavelength at 1551.72 nm is used as the light source and then an intensity Mach-Zehnder modulator (MZM) is used to convert the electrical signals to optical signals, and an optical bandwidth pass filter (OBPF) can be used to generate single-sideband signals. The bias point and p-p voltage of the MZM are 0.5 and 0.2, respectively. The symbol rate of SCMA-OFDM signal is 8.5-GBaud/s. Considering the overload factor is 1.5 and each codeword is labeled by 2 bits, the signal rate is 25.5- Gb/s. 102-Gb/s capacity can be achieved by stacking four wavelengths with 25.5-Gb/s bit rate on each. The modulated optical signal propagates through a fiber optic link, which is emulated with 20/60km single mode fiber. The Loss and dispersion parameters are set to be 0.2 dB/km and 16 ps/(nm∗km), respectively. A variable optical attenuator and a

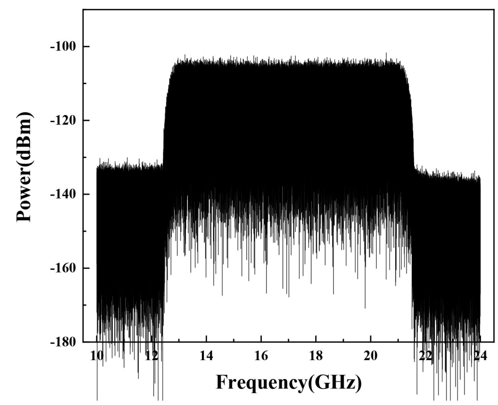

Fig. 5. The frequency spectra with a P_r of -4 dBm over 20-km SMF.

1:2 splitter is placed after the fiber for BER measurement. At the receiver, a photodiode converts the optical signal to an electrical current through square law detection. The ShotNoise is on and the thermal noise is set to be 1e^{-12}A/H_z^ (1/2). Fig. 5 depicts the electrical spectra after 20-km SMF with -4-dBm received power. We can see that the 3-dB bandwidth is about 8.4-GHz. The electrical signal is then down-converted to baseband and off-line processed using MATLAB and Python. The received signals are transformed into the frequency-domain by FFT. In MPA-based scheme, the pilots are extracted for channel estimation, and then the distorted data are compensated by one-tap equalizer and detected by MPA algorithm. In the GNN-based receiver (Rx), channel estimation, channel equalization and QAM demapping are replaced by the GNN model. In the training phase, 348000 bits of each ONU by different random seed is generated. The ratio of training dataset and test dataset is 7:3. The length of the whole data sets is 1044000, 730800 symbols for training and 313200 for test.

Figs. 6 -8 shows the average BER performance of MPA- and GNN-based Rxs with the transmitted power (P_t) 0-dBm under back-to-back, 20-km SMF and 60-km SMF SSB transmission, respectively. It can be seen that when setting the number of iterations and filters as two and ten respectively, the performance of GNN-based Rx is slightly worse than that of MPA because the learning ability of the GNN model is insufficient. With the increase of the number of iterations and filters, the model has stronger learning and fitting ability and GNN-based Rx shows better performance than that of MPA. For GNN-based

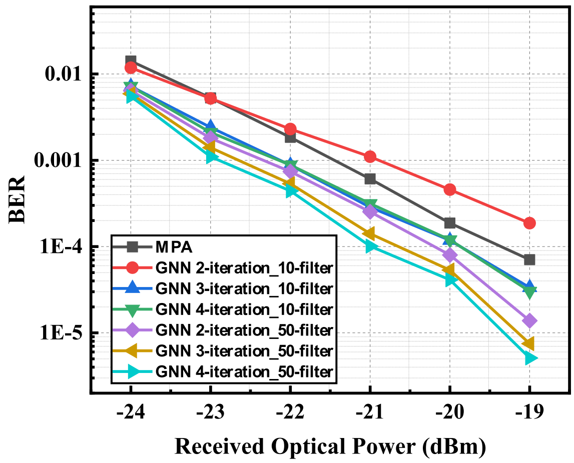

Fig. 6. BER performance vs. P_r for back-to-back transmission with a P_t of 0-dBm.

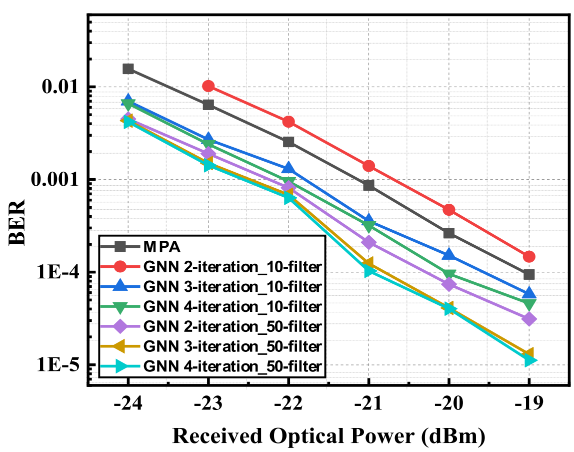

Fig. 7. BER performance vs. P_r after 20-km SMF with a P_t of 0-dBm.

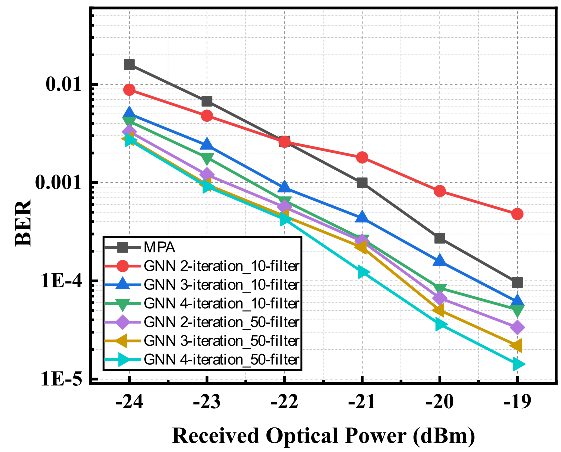

Fig. 8. BER performance vs. P_r after 60-km SMF with a P_t of 0-dBm.

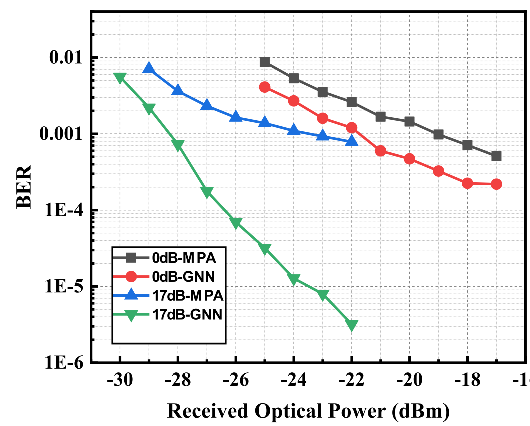

Fig. 9. BER performance vs. P_r after DSB 60 km SMF.

Rx with 3-iterations and 10-filters, the required received optical power (P_r) to achieve a BER of $1*10^{-3}$ is about -23-dBm for back-to-back transmission and 60-km SMF with negligible power penalty. And we can see GNN-based Rx can improve the BER performance by about 2-dB for 60-km SMF transmission compared with MPA-based Rx. This occurs due to the knack of GNN to obtain the gain of channel compensation and multi-user demapping in one shot.

Then, the performance of MPA- and GNN-based Rxs in the case of double-sideband transmission is also compared. The symbol rate of SCMA-OFDM signal is 5-GBaud/s and the frequency of up conversion is 5-GHz. The GNN model is with 3-iteration and 10-filters. The average BER performance of MPA and GNN as a function of P_r over 60-km SMF with a P_t of 0-dBm and 14-dBm is depicted in Fig. 9. When the P_t is 0-dBm, the P_r to achieve the BER of $1*10^{-3}$ are about -19 dBm and -22 dBm for MPA- and GNN-based Rxs, respectively. The better BER performance of GNN is mainly due to higher robustness again chromatic dispersion. For SCMA-OFDM transmission, increasing transmit optical power and the fiber length will bring higher levels of nonlinear distortions. At the BER limit of $1*10^{-3}$, increasing Pt by 14-dB results in power penalties of about 4- and 6.5-dB for the MPA- and GNN-based Rxs, respectively. It can be seen that GNN-based method can perform impairment compensation better and have high robustness again nonlinearity.

Furthermore, the computational complexity of GNN-based Rx is discussed. To extract the features in non-Euclidean data structure, GNN requires a large number of observed data to train the model, which might be high consuming in terms of required computational resources. Nonetheless, the optical links in PON have relatively stable channel parameters, the model training could be accomplished once [29]. In this paper, we mainly consider the computational complexity of prediction online in terms of the number of multiplications. Let V_N be the number of user nodes, d_v be the number of subcarriers occupied by each user, d_f be the number of users carried by each carrier, N_f represent the number of filters, r be the number of iterations, a be the load factor and M represent the modulation order. The complexity of MPA can be written as:

$$\begin{aligned} r(d_f-1)V_N d_f M^{d_f}/a + r(d_v-1)V_N d_v M \\ + r d_v V_N + r d_f V_N + V_N M^{d_f}/a \end{aligned} \tag{9}$$

The complexity of GNN is given by

$$4V_N d_v N_f + (2r-1) d_v V_N N_f^2 \tag{10}$$

TABLE I
THE COMPUTATIONAL COMPLEXITY OF GNN AND MPA

	MPA	**GNN (2-layer and 10-filter)**	**GNN (3-layer and 10-filter)**	**GNN (4-layer and 10-filter)**
Multiplications	6748	4080	6480	8880
		GNN (2-layer and 50-filter)	**GNN (3-layer and 50-filter)**	**GNN (4-layer and 50-filter)**
Multiplications		92400	152400	212400

According to (9) and (10), Table I shows the number of multiplication operations of GNN and MPA in our simulation. When three iterations and ten filters are adopted in GNN, its complexity is close to that of MPA. And we can see that the complexity of GNN increases linearly with the increase of the number of users when the model layer and load rate are fixed. Increasing the number of filters and iterations continuously will not evidently improve the performance in our evaluations, but will lead to a higher complexity. By choosing appropriate model parameters, the balance between transmission performance and complexity can be achieved.

IV. CONCLUSION

The applicability of deep learning method that operates on graph domain for multi-user detection in long reach SCMA-PON is investigated in this paper. A specially designed GNN is proposed to decode the multiplexed signal directly without channel estimation. The results show that the GNN-based Rx offered improved BER performance and higher robustness against nonlinear distortion compared with the MPA-based Rx. After 60-km SSB SMF transmission, the performance gain is about 2-dB for the same level of computational complexity. With the increase of transmit optical power and transmission length, GNN can have maximum available 2.5-dB performance gain for DSB 60-km SMF transmission.

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