

Extreme Mobile Broadband Tier-II Fronthaul Network Enabled by a New DNN Machine Learning Framework

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Abstract: We propose a new DNN framework for the next-generation mobile fronthaul network supporting tier-II enhanced mobile broadband. The mobile fronthaul network integrates the GPU for efficient resource-saving machine learning. In addition, the framework can achieve over 30% relative capacity improvement.

1. Introduction

Machine Learning techniques have been known as the primary driving force for the coming Fourth Industrial Revolution [1]. Recently, both academia and industry put together heroic efforts in delivering new machine learning methodology as well as parallel computing hardware. New optimization algorithms like SGD [2] and Adamax [3] have dramatically facilitated the robustness and efficiency of model training. Besides, advanced hardware like Tensor Processing Unit (TPU) by Google and Graphic Processing Unit (GPU) by Nvidia provide the robust platform for parallel computing execution [4-5]. Neural networks are the most popular methodology for machine learning due to their robust modeling capability especially those with several hidden layers. Neural network based techniques have already shown their strength in the field of natural language processing and computer vision [6-7]. However, their applications into Mobile Fronthaul (MFH) are still new. Due to the rising data-demand through mobile access, and the broader RF spectrum resource exploitation of the coming 5G new-radio (5G-NR) system, technical and conceptual revolutions are redefining the next-generation MFH network [8]. From the released 5G-NR specifications by 3GPP, three primary use cases are defined, including enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable low-latency communication (URLLC). Since eMBB is targeting the larger network capacity and the higher peak data rate, neural-network becomes an excellent candidate satisfying the eMBB demands. Therefore, we propose the new framework for the next-generation MFH supporting eMBB.

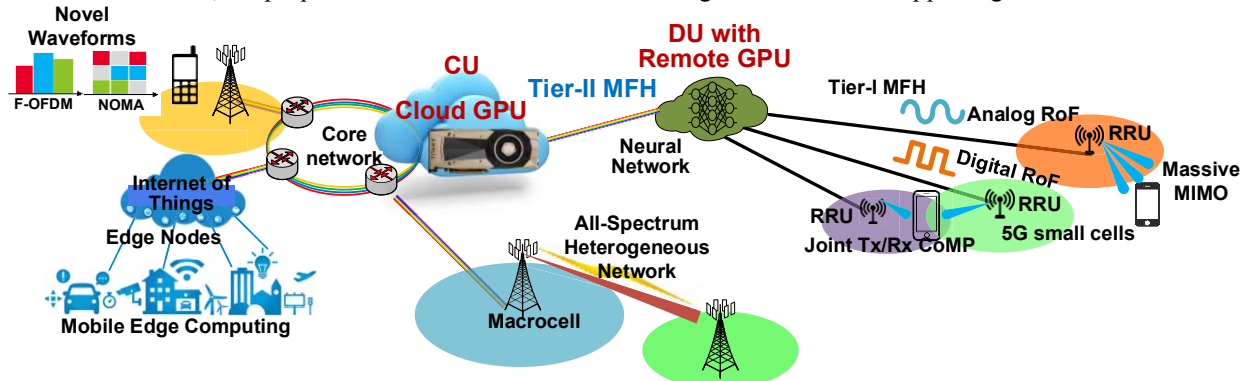


Figure 1. Proposed machine learning framework of the next-generation mobile fronthaul network.

2. Research Results

A conceptual diagram of next-generation MFH network implementing neural network is illustrated in Fig. 1. The MFH network consists of the central unit (CU), distributed unit (DU) and remote radio unit (RRU) [9-10]. The neural network can be designed for realizing signal equalization or decoding in tier-II MFH transmission connecting the CU and DU. Here, we for the first time propose an innovative framework, namely cloud GPU in CU and remote GPU in DU. Due to the massive number of parameters in a deep neural network, the model training from scratch to the optimum is resource consuming. Shifting the initial training load to the CU with the powerful cloud GPU station will be an efficient solution. Once the initial training is completed, the model can be passed down to the DU for adaptive training to tackle the dynamic channel environment. There are three major types of neural network, which are the deep

neural network (DNN), convolutional neural network (CNN) and recurrent neural network (RNN) [11]. The design and combination of the DNN, CNN, and RNN depend on the specific task goal.

The DNN signal recovery mechanism is implemented at the DU to decode the received signal from the CU. As shown in Fig.2(a), the DNN takes the received sample with its previous L , and subsequently, L samples as the input. K hidden layers are added to improve the model fitting capability. At the output layer, the number of neurons depends on the specific modulation scheme. For example, PAM-M corresponds to M output neurons. ReLU activation function, which is known for fast converging and ability to avoid gradient vanishing, is incorporated in each neuron of the hidden layers. Softmax activation function is used at the output layer for classification, while loss function is defined as categorical-crossentropy.

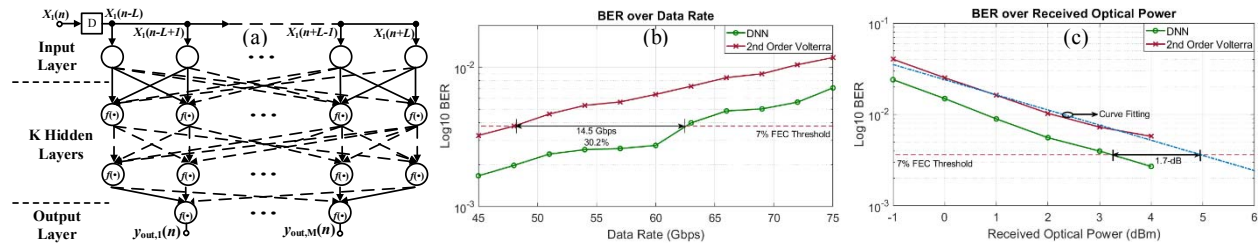


Figure 2. (a) K hidden layers PAM-M decoding deep neural network. BER over (b) data rate, (c) ROP comparison.

In the experiment, we prove the framework's functionality using an intensity-modulation direct-detection (IMDD) system. A 20-Gbaud random PAM-8 signal with 256-K symbol length is generated through a 65-GSa/s arbitrary waveform generator (AWG) and modulated onto a directly modulated laser in the CU. The modulated optical signal is then fed into a 30-km standard single mode fiber (SSMF) and detected by a PIN photodetector in the DU for optical to electrical conversion. An 80-GSa/s oscilloscope samples the electrical signal for offline digital signal processing. After down-sampling and synchronization, the first 64 K received samples are used as the training set of the DNN. The cloud GPU trains the initial optimized model, and then the remote GPU uses the pre-trained model for further training to adapt the channel variations. We experimentally compare the BER performance between the DNN and the 2nd order Volterra over different data rate/received optical power (ROP). In Fig. 2(b), a 14.5-Gbps gain is achieved, corresponding to 30.2% relative capacity improvement. Besides, the DNN demonstrates a 1.7-dB sensitivity gain at the 7% overhead FEC-HD threshold as shown in Fig. 2(c). A 60 Gb/s over 30-km SSMF tier-II MFH transmission based on an IM-DD system without dispersion compensation using the neural network is thus experimentally proved.

3. Conclusions

In this paper, we have experimentally demonstrated the efficacy of neural network's implementation into the next-generation MFH network between CU and DU. The proposed novel MFH framework achieved over 30% relative capacity improvement. The framework shifts the machine-learning burden to the cloud GPU of the CU, with minimum training resource required at the DU to tackle small channel variance. Along with recent progress in machine-learning algorithm and hardware, this new framework will be beneficial to enable extreme mobile broadband services.

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