Federated Deep Learning Framework For Hybrid Beamforming in mm-Wave Massive MIMO

Ahmet M. Elbir, Senior Member, IEEE, and Sinem Coleri, Senior Member, IEEE

Abstract—Machine learning (ML) for wireless communications requires the training of a global model with a large dataset collected from the users. However, the transmission of a whole dataset between the users and the base station (BS) is computationally prohibitive. In this work, we introduce a federated learning (FL) based framework where the model training is performed at the BS by collecting only the gradients from the users. In particular, we design a convolutional neural network (CNN), whose input is the channel data and it yields the analog beamformers at the output. We have evaluated the performance of the proposed framework via numerical simulations and shown that FL is more tolerant than ML to the imperfections and corruptions in the channel data as well as having less complexity.

Index Terms—Deep learning, Federated learning, Hybrid beamforming, massive MIMO.

I. INTRODUCTION

In mm-Wave massive MIMO (multiple-input multiple-output) systems, the users estimate the downlink channel and corresponding beamformers, then feedback to the base station (BS) via uplink channel with limited feedback techniques [1]. Hence, several hybrid beamforming approaches are proposed in the literature [1], [2]. However, the performance of these approaches strongly relies on the perfectness of the channel state information (CSI). To provide a robust beamforming performance, data-driven approaches, such as machine/deep learning (ML/DL), are proposed [3], [4].

In the context of ML, a neural network (NN) model at the BS is trained with the training data collected by the users (see Fig. 1). This process requires the transmission of each user’s data to the BS. Therefore, the data collection and transmission introduce huge complexity, which brings a major challenge for ML researcher in the communications society. To alleviate these drawbacks, federate learning (FL) strategies are recently introduced, especially for edge computing applications [5]. In FL, instead of collecting the data itself from the edge devices (mobile users), they only transmit the gradient information of the NN model to the BS where the NN is iteratively trained by using stochastic gradient descent (SGD) algorithm [6]. While this approach introduces the complexity of computation of gradients at the edge devices, transmitting only the gradient information has significantly lower complexity rather than sending the whole training dataset from each user.

Although FL is a very efficient way of designing an ML framework for wireless communication, it is mostly considered for the applications of wireless sensor networks, e.g., UAV (unmanned aerial vehicle) networks [7], [8], vehicular networks [9]. In [7], the authors apply FL to the trajectory planning problem where a UAV swarm is employed and the data collected by each UAV are processed for gradient computation and a global NN at the “leading” UAV is trained. In [8] and [9], client scheduling and power allocation problems are investigated for FL framework respectively. Different from [7]–[9], [10] considers a more realistic scenario where the gradients are transmitted to the BS through a noisy wireless channel and a classification model is trained for image classification. Notably, to the best of our knowledge, the application of FL for massive MIMO hybrid beamforming is not investigated in the literature. Furthermore, above works mostly consider simple ML structures which accommodate shallow NN architectures such as a single layer NN [10]. The performance of these architectures can be leveraged by utilizing deeper NNs such as convolutional neural networks (CNNs) [4], which also motivates us to exploit DL architectures for ML in this work.

In this letter, we propose a federated deep learning (FDL) framework for hybrid beamforming. We design a CNN architecture employed at the BS. The CNN accepts the input of channel matrix and it yields the RF beamformer at the output. The deep network is then trained by using the gradient data collected from the users. Each user computes the gradient information with its available training data (a pair of channel matrix and corresponding beamformer index), then sends it to the BS. The BS receives the whole gradient data from the users and performs parameter update for the CNN model. Compared to the conventional ML/DL works [4], [11], [12], this approach is advantageous due to its low transmission overhead. Because, the size of the training data that the users need to send is much larger than the size of the model parameters (see, e.g., Fig. 1). We have shown, through numerical simulations, that the proposed FL approach provides much less complexity and it exhibits reasonable beamforming performance.

A. M. E. is with the Department of Electrical and Electronics Engineering, Duzce University, Duzce, Turkey (e-mail: ahmetmelbir@gmail.com).
S. C. is with the Department of Electrical and Electronics Engineering, Koc University, Istanbul, Turkey (e-mail: sergen@ku.edu.tr).
II. SIGNAL MODEL AND PROBLEM DESCRIPTION

We consider a multi-user MIMO scenario where the BS communicates with $K$ single-antenna users. In the downlink, we assume that the BS has $N_T$ antennas and it first precodes $K$ data symbols $s = [s_1, s_2, \ldots, s_K]^T \in \mathbb{C}^K$ by applying baseband precoders $F_{BB} = [F_{BB,1}, \ldots, F_{BB,K}] \in \mathbb{C}^{N_T \times K}$. Then, the BS employs $K$ RF precoders $F_{RF} = [F_{RF,1}, \ldots, F_{RF,K}] \in \mathbb{C}^{N_s \times K}$ to form the transmitted signal. Given that $F_{RF}$ consists of analog phase shifters, we assume that the RF precoder has constant unit-modulus elements, i.e., $\|F_{RF}\|_2 = 1$ and we have $\|F_{RF}F_{BB}\|_2 = K$. Thus, the $N_T \times 1$ transmit signal is $x = F_{RF}F_{BB}s$, and the received signal at the $k$-th user becomes $y_k = h_k^H \sum_{n=1}^{K} F_{RF}F_{BB,n}s_n + n_k$, where $h_k \in \mathbb{C}^{N_T}$ denotes the mm-Wave channel for the $k$-th user with $\|h_k\|_2 = N_T$ and $n_k \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN) vector.

We adopted clustered channel model where the mm-Wave channel $h_k$ is represented as the cluster of $L$ line-of-sight (LOS) received path rays [1], [2], i.e.,

$$h_k = \beta \sum_{l} \alpha_{k,l} a(\varphi(k,l)), \quad (1)$$

where $\beta = \sqrt{N_T/L}$ and $\alpha_{k,l}$ is the complex channel gain. $a(\varphi(k,l)) \in [\frac{\varphi(k,l)}{\pi \sqrt{L}}]$ denotes the direction of the transmitted paths. $a(\varphi(k,l))$ is the $N_T \times 1$ analog steering vector whose $m$-th element is given by $a_{m}(\varphi(k,l)) = \exp\left(-j \frac{2\pi}{\lambda} d (m - 1) \sin(\varphi(k,l))\right)$, where $\lambda$ is the wavelength and $d$ is the array element spacing.

Assuming Gaussian signaling, then the achievable rate for the $k$-th user is $R_k = \log_2 \left[ 1 + \frac{1}{\pi} \sum_{m=1}^{K} |h_k^H F_{BB,n} s_n|^2 + \sigma^2 \right]$ and the sum-rate is $R = \sum_{k \in K} R_k$ for $K = \{1, \ldots, K\}$ [1].

Let us denote the parameter set of the global DL network at the BS as $\theta \in \mathbb{R}^P$ which has $P$ real valued learnable parameters. Then, the DL network can be represented as a nonlinear relationship between the input $\mathcal{X}$ and output $Y$ as $f(\theta; \mathcal{X}) = Y$.

In this work, we focus on the training stage of the global NN model. Therefore, we assume that each user has available training data pairs, e.g., the channel vector $h_k$ and the corresponding RF precoder $f_{RF,k}$, which can be obtained by both DL [4], [13] and non-DL [2] algorithms.

Thus, the aim in this work is to learn $\theta$ by training the global NN with the available training data available at the users. Once the learning stage is completed, then each user can predict their corresponding RF precoder by feeding the NN with the channel data, then feed it back to the BS.

III. FDL FOR HYBRID BEAMFORMING

Let us denote the training dataset for the $k$-th user as $\mathcal{D}_k = \{ (\mathcal{X}_k^{(1)}, Y_k^{(1)}), \ldots, (\mathcal{X}_k^{(D_k)}, Y_k^{(D_k)}) \}$ where $\mathcal{D}_k = |\mathcal{D}_k|$ is the size of the dataset and we have $\mathcal{X} = \cup_{k \in K} \mathcal{X}_k$, $\mathcal{Y} = \cup_{k \in K} \mathcal{Y}_k$. In conventional ML-based works [3], [4], [13], [14], the training of the global model is performed at the BS by collecting the datasets of all users (see Fig. 1). Once the BS collects $\mathcal{D} = \bigcup_{k = 1}^{K} \mathcal{D}_k$, the global model is trained by minimizing the empirical loss,

$$F(\theta) = \frac{1}{D} \sum_{i=1}^{D} \mathcal{L}(f(\theta; \mathcal{X}^{(i)}), Y^{(i)}), \quad (2)$$

where $D = |\mathcal{D}|$ is the size of the training dataset and $\mathcal{L}(\cdot)$ is the loss function defined by the learning model. The minimization of (2) is achieved by updating the model parameters via gradient descent (GD) iteratively, e.g., at iteration $t$ we have $\theta_{t+1} = \theta_t - \eta_t \nabla F(\theta_t)$, where $\eta_t$ is the learning rate at $t$. However, for large datasets, the implementation of GD is computationally prohibitive. To reduce the complexity, SGD technique is used where $\theta_t$ is updated by $\theta_{t+1} = \theta_t - \eta_t\nabla g(\theta_t)$, which satisfies $\mathbb{E}(g(\theta_t)) = \nabla F(\theta_t)$. Therefore, SGD allows us to minimize (2) by partitioning the dataset into multiple portions. In conventional ML, SGD is mainly used to accelerate the learning process by partitioning the training dataset into batches, which is known as batch learning [6]. In FL, the training dataset is partitioned into small portions, however they are available at the edge devices. Hence, $\theta_t$ is updated, by collecting the local gradients $\{g_k(\theta_t)\}_{k \in K}$ computed at users with their own datasets $\{\mathcal{D}_k\}_{k \in K}$. Thus, the BS incorporates $\{g_k(\theta_t)\}_{k \in K}$ to update the global model parameters as

$$\theta_{t+1} = \theta_t - \eta_t \frac{1}{K} \sum_{k=1}^{K} g_k(\theta_t), \quad (3)$$

where $g_k(\theta_t) = \frac{1}{|\mathcal{D}_k|} \sum_{i=1}^{\mathcal{D}_k} \nabla \mathcal{L}(f(\theta_t; \mathcal{X}_k^{(i)}, Y_k^{(i)}))$ is the stochastic gradient computed at the $k$-th user with $\mathcal{D}_k$.

Due to the limited number of users, $K$, there will be deviations in the gradient average $\frac{1}{K} \sum_{k=1}^{K} g_k(\theta_t)$ from the stochastic average $\mathbb{E}(g(\theta_t))$. To reduce the oscillations due to the gradient averaging, parameter update is performed by using a momentum parameter $\gamma$ which allows us to “moving-average” the gradients [6]. Finally, the parameter update with momentum is given by

$$\theta_{t+1} = \theta_t - \eta_t \frac{1}{K} \sum_{k=1}^{K} g_k(\theta_t) + \gamma(\theta_t - \theta_{t-1}). \quad (4)$$

A. Data Acquisition

In this part, we discuss how the acquisition is done for training process. We design the input of the NN as a real-valued three “channel” tensor, i.e., $\mathcal{X}_k \in \mathbb{R}^{\sqrt{N_T} \times \sqrt{N_T} \times 3}$. Hence, we first reshape the channel vector by using a function $\Pi(\cdot) : \mathbb{R}^{N_T} \rightarrow \mathbb{R}^{\sqrt{N_T} \times \sqrt{N_T}}$ as $H_k = \Pi(h_k)$, which concatenates the $\sqrt{N_T} \times 1$ sub-columns of $h_k$ into a matrix [1]. Then, for the $k$-th user, we construct the first and the second “channel” of input data as $[\mathcal{X}_k]_1 = \text{Re}(H_k)$ and $[\mathcal{X}_k]_2 = \text{Im}(H_k)$ respectively. Also, we select the third “channel” as element-wise phase value of $H_k$ as $[\mathcal{X}_k]_3 = \angle(H_k)$.

We use “three-channel” input in order to improve the input feature representation [3], [13]. The output of the NN is designed with a classification layer. To do so, we first divide the angular domain $\Theta = [-\pi/2, \pi/2]$ into $Q$ equally-spaced non-overlapping subregions.

1We use 2-D input data since it provides better feature representation for convolutional layers. We assume that $\sqrt{N_T}$ is an integer value, if not, $H_k$ can always be constructed as a rectangular matrix.
\( \Theta_q = [\varphi_q^{\text{start}}, \varphi_q^{\text{end}}] \) for \( q \in Q = 1, \ldots, Q \). Hence, we have \( \Theta = \cup_{q \in Q} \Theta_q \). As a result, there are \( Q \) classes used to label the whole dataset. For example, let us assume that the \( k \)-th user is located in \( \Theta_q \). Then we represent the channel data \( h_k \) as label \( q \), i.e., \( \mathcal{Y}_k = q \). We design the RF precoder corresponding to the \( k \)-th user as the steering vector towards \( \Theta_q \). In other words, \( f_{R, k} \) is constructed as \( a(\varphi_q) \) where \( \varphi_q = \frac{\varphi_q^{\text{start}} + \varphi_q^{\text{end}}}{2} \).

After training, each user has access the learned global model \( \theta \). Hence, they simply feed the NN with \( h_k \) to obtain \( \tilde{\varphi}_q \) and construct the analog beamformer \( f_k \). Once, the BS has \( F_{RF} \), the baseband beamformer \( F_{BB} \) can be designed accordingly to suppress the user interference [1].

**B. Deep Network Architecture**

The global DL model is comprised of 11 layers with two convolutional layers (CLs) and a single fully connected layer (FCL). The first layer is the input layer of size \( \sqrt{N_T} \times \sqrt{N_T} \times 3 \). The second and the fifth layers are CLs, each of which has \( N_{CL} = 256 \) filters of size \( 3 \times 3 \). The eighth layer is an FCL which has \( N_{FCL} = 512 \) units. After each CL, there is a normalization layer following a ReLU layer, i.e., \( \text{ReLU}(x) = \max(0, x) \). The ninth layer is a dropout layer with 50% probability factor after the FCL. The tenth layer is a softmax layer defined for an arbitrary input \( \bar{x} \in \mathbb{R}^D \) as \( \text{softmax}(\bar{x}) = \frac{\exp(x_i)}{\sum_{i=1}^{D} \exp(x_i)} \). Finally, the output layer is the classification layer of size \( Q \).

**IV. Numerical Simulations**

In this section, we evaluate the performance of the proposed FDL approach via numerical simulations. The proposed DL model is realized and trained in MATLAB on a PC with a single GPU and a 768-core processor. We used the stochastic gradient descent algorithm with momentum \( \gamma = 0.9 \) and updated the network parameters with learning rate 0.001. The mini-batch size for DL training is 128. We generated \( N = 500 \) different channel realizations for each user, which are randomly located in \( \left[ \frac{-\pi}{2}, \frac{\pi}{2} \right] \) with \( L = 5 \) paths and angle spread of \( \sigma_{\varphi} = 3^\circ \). We assume that the BS has \( N_T = 100 \) antennas with \( d = \frac{\lambda}{2} \) and there are \( K = 8 \) users, unless stated otherwise. Then, we add synthetic AWGN into each channel data for \( G = 100 \) realizations with respect to \( \text{SNR}_{\text{TRAIN}} = 20 \log_{10}(\frac{\|H_{\text{train}}\|^2}{\sigma_n^2}) \) to reflect the imperfect channel conditions and we select \( \text{SNR}_{\text{TRAIN}} = \{15, 20, 25\} \) dB. Hence, the total number of the training data size is \( 10 \times 10 \times 3 \times \text{D} \) where \( \text{D} = (3 \cdot N \cdot G \cdot K) = 1,200,000 \). Finally, we select the number of classes as \( Q = 360 \). In the training process, 80% and 20% of the whole data are used in training and validation respected. Once the training is completed, validation data is used in prediction stage. However, we add a synthetic noise into the validation data by \( \text{SNR}_{\text{TEST}} \) to represent the imperfect channel data.

In Fig. 2 we present the training performance of DL and FDL for hybrid beamforming for both uniformly (Fig. 2(a)) and non-uniformly distributed users (Fig. 2(b)). The uniform distribution means that the each user’s location is randomly drawn from the whole angular space for each generated channel data. Since this scenario is not realistic, i.e., users cannot move along such a large distance for data collection stage, we also provide the non-uniform distribution, i.e., each user’s location is in a subregion of the angular domain. Therefore, it is assumed that the angular domain is divided into \( K \) subregions with \( 5^\circ \) overlap, in each of which there is a single user. For DL and FDL, training is performed for the same NN with the same training dataset. Except, in FDL, the training data is partitioned into \( K \) and the weight update is done by using the averaged gradients as in [4]. We present the results for different number of users while keeping the dataset size fixed as \( \text{D} = 1,200,000 \) by selecting \( G = 100 \cdot \frac{\pi}{\sigma_{\varphi}} \). In Fig. 2(a)-b, we provide the validation accuracy of all dataset \( \text{D} \) for \( K = \{2, 4, 8\} \). In addition, we also present the accuracy of each user’s dataset \( D_k \) in dashed curves to show the deviations from the accuracy of whole data. As it is seen, the training process reaches convergence longer as \( K \) increases. Also we can see that dataset with uniform distribution provides faster convergence for FDL since in the non-uniform case the weight update becomes harder if the training data of each user is different than the other’s. In particular, the weights obtained by training each user’s dataset cause deviations in the model weights. This can be observed from the large deviations of the dashed curves, the accuracy of each user’s dataset. We can see the the deviations become larger as \( K \) increases. However, we do not observe such behavior for DL since it uses the whole dataset at once.

In Fig. 2(c), we present the accuracy for corrupted channel
data, which is introduced by $\text{SNR}_{\text{TEST}}$ defined similar to $\text{SNR}_{\text{TRAIN}}$. We assume that the users are non-uniformly distributed as discussed above. As it is seen, FDL is more tolerant to the imperfect channel while their accuracies are similar in Fig. 2(a)-(b). This is due to the update rule of FDL which is optimized for each user’s dataset at each iteration. As a result, FDL becomes more robust against the imperfections in the input channel data. We also see that the performance of FDL becomes better when $K$ is small.

In Fig. 3 we present the rate for the proposed FDL framework in comparison with both DL-based MLP (multilayer perceptron) [3] and non-DL-based SOMP (spatial orthogonal matching pursuit) [2] techniques for $\text{SNR}_{\text{TEST}} = 5$ dB. We can see that the proposed approach provides higher performance as compared to the competing algorithms. The outperformance of FL can be attributed to the robustness against the changes/deviations in the channel data as compared to the techniques based on conventional DL training.

Finally, we present the complexity performance of FDL and conventional DL. In particular, we compare the size of data required to be sent to the BS. Hence, the complexity of FDL is fixed as the total number of learnable parameters of CNN, which is given by 
\[ P = 2(CN_{\text{CL}}W_xW_y) + N_{\text{CL}}W_xW_y \left( \frac{50}{100} \right), \]
where $C = 3$ is the number of “channels” and $W_x = W_y = 3$ are the 2-D size of each filter. Consequently, we have $P = 13824 + 589824 = 603648$ and observe that CLs provide efficient way of reducing the network size in comparison with FCL. On the other hand, the complexity of DL is due to the size of the dataset which is $D = 3 \cdot N \cdot G \cdot K$. In Fig. 4 we present the complexity of FDL and DL with respect to $N_T$ for different $G$ values. In addition we set the complexity of FDL to $30 \cdot 603648 = 18109440$ where we assume training takes 30 iterations. As it is seen, FDL provides fixed and lower complexity than DL. In particular, FDL is efficient than ML on the order of magnitude of $\{6.7, 13.4, 20.1\}$ for $G = \{100, 200, 300\}$ respectively.

V. SUMMARY

In this work, we have proposed a deep federated learning strategy for hybrid beamforming problem. FDL is advantageous since it does not require the training dataset to be sent to the BS for model training. Instead, only the gradient information to update the NN weights.

REFERENCES

[1] A. Alkhateeb, G. Leus, and R. W. Heath, “Limited feedback hybrid precoding for multi-user millimeter wave systems,” IEEE Transactions on Wireless Communications, vol. 14, no. 11, pp. 6481–6494, 2015.
[2] O. E. Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, “Spatially sparse precoding in millimeter wave MIMO systems,” IEEE Trans. Wireless Commun., vol. 13, no. 3, pp. 1499–1513, 2014.
[3] H. Huang, Y. Song, J. Yang, G. Gui, and F. Adachi, “Deep-learning-based millimeter-wave massive MIMO for hybrid precoding,” IEEE Trans. Veh. Technol., vol. 68, no. 3, pp. 3027–3032, 2019.
[4] A. M. Elbir and A. Papazafeiropoulos, “Hybrid Precoding for Multi-User Millimeter Wave Massive MIMO Systems: A Deep Learning Approach,” IEEE Trans. Veh. Technol., vol. 69, no. 1, p. 552563, 2020.
[5] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, “Wireless network intelligence at the edge,” Proceedings of the IEEE, vol. 107, no. 11, pp. 2204–2239, 2019.
[6] D. Alistarh, D. Grubic, J. Li, R. Tomioka, and M. Vojnovic, “QSGD: Communication-efficient SGD via gradient quantization and encoding,” in Advances in Neural Information Processing Systems, 2017, pp. 1709–1720.
[7] T. Zeng, O. Semiari, M. Mozaffari, M. Chen, W. Saad, and M. Bennis, “Federated Learning in the Sky: Joint Power Allocation and Scheduling with UAV Swarms,” arXiv preprint arXiv:2002.08196, 2020.
[8] M. M. Wadu, S. Samarakoon, and M. Bennis, “Federated learning under channel uncertainty: Joint client scheduling and resource allocation,” arXiv preprint arXiv:2002.00802, 2020.
[9] S. Samarakoon, M. Bennis, W. Saad, and M. Debbah, “Federated learning for ultra-reliable low-latency v2v communications,” in 2018 IEEE Global Communications Conference (GLOBECOM), 2018, pp. 1–7.
[10] M. Mohammadi Amiri and D. Gnzd, “Machine learning at the wireless edge: Distributed stochastic gradient descent over-the-air,” IEEE Trans. Signal Process., vol. 68, pp. 2155–2169, 2020.
[11] X. Li and A. Alkhateeb, “Deep learning for direct hybrid precoding in millimeter wave massive mimo systems,” in 2019 53rd Asilomar Conference on Signals, Systems, and Computers, 2019, pp. 800–805.
[12] J. Tao, J. Xing, J. Chen, C. Zhang, and S. Fu, “Deep Neural Hybrid Beamforming for Multi-User mmWave Massive MIMO System,” in 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Nov 2019, p. 15.
[13] A. M. Elbir and K. V. Mishra, “Online and Offline Deep Learning Strategies For Channel Estimation and Hybrid Beamforming in Multi-Carrier mm-Wave Massive MIMO Systems,” arXiv preprint arXiv:1912.10036, 2019.
[14] A. M. Elbir and K. V. Mishra, “Joint antenna selection and hybrid beamformer design using unquantized and quantized deep learning networks,” IEEE Trans. Wireless Commun., vol. 19, no. 3, pp. 1677–1688, March 2020.