Artificial Intelligence-aided OFDM Receiver: Design and Experimental Results

Peiwen Jiang, Tianqi Wang, Bin Han, Xuanxuan Gao, Jing Zhang, Chao-Kai Wen, Shi Jin, and Geoffrey Ye Li

Abstract

Orthogonal frequency division multiplexing (OFDM) is one of the key technologies that are widely applied in current communication systems. Recently, artificial intelligence (AI)-aided OFDM receivers have been brought to the forefront to break the bottleneck of the traditional OFDM systems. In this paper, we investigate two AI-aided OFDM receivers, data-driven fully connected-deep neural network (FC-DNN) receiver and model-driven ComNet receiver, respectively. We first study their performance under different channel models through simulation and then establish a real-time video transmission system using a 5G rapid prototyping (RaPro) system for over-the-air (OTA) test. To address the performance gap between the simulation and the OTA test caused by the discrepancy between the channel model for offline training and real environments, we develop a novel online training strategy, called SwitchNet receiver. The SwitchNet receiver is with a flexible and extendable architecture and can adapts to real channel by training one parameter online. The OTA test verifies its feasibility and robustness to real environments and indicates its potential for future communications systems. At the end of this paper, we discuss some challenges to inspire future research.

Index Terms

Artificial intelligence, DNN, OFDM, SwitchNet, OTA.

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I. INTRODUCTION

By introducing artificial intelligence (AI), intelligent communications can potentially address many challenging issues in traditional communication systems. There have been many achievements in intelligent communications recently [1], [2], [3], including using AI for signal classification [4], multiple-input multiple-output (MIMO) detection [5], channel state information (CSI) feedback [6], [7], novel autoencoder-based end-to-end communication systems [8] and [9].

Orthogonal frequency division multiplexing (OFDM) has been proved to be an effective technique to deal with delay spread of wireless channels [10], [11]. OFDM receivers can be classified into two categories: linear and nonlinear receivers. Linear receivers include least square (LS) [12], [13] and minimum mean-squared error (MMSE) [14] for channel estimation (CE) or signal detection (SD) while nonlinear receivers contain approximate-message-passing (AMP) [15] and expectation-propagation (EP)-based algorithms [16]. These receivers are all designed based on expert knowledge or specific models.

Recently, Ye et al. [17] have proposed a novel data-driven AI-aided OFDM receiver that uses a fully connected-deep neural network (FC-DNN) to detect data directly after fast Fourier transformation (FFT) module. By treating joint channel estimation and signal detection as a black box, the AI-aided OFDM receiver exploits no expert knowledge of wireless communications and trains all parameters with a large amount of wireless data by stochastic gradient descent (SGD)-based algorithms. The data-driven AI-aided OFDM receiver in [17] is proved to be robust to the impact of pilot reduction, CP omission, and nonlinear clipping noise, but it converges slowly and is with high computational complexity. Inspired by [17], other data-driven methods [18], [19] have been also developed recently.

AI algorithms can exploit expert knowledge to develop model-driven AI approaches. In [20], one of earliest model-driven AI approaches has been proposed for magnetic resonance imaging (MRI). Now the model-driven AI approaches have been extended to wireless physical layer by designing the network architecture based on wireless physical domain knowledge [3] and have been proved to be promising to address the aforementioned problems. In particular, a model-driven based AI-aided OFDM receiver, called ComNet, has been proposed in [21]. Instead of using a single deep neural network (DNN) to detect signals with implicit CE as the FC-DNN receiver [17], the ComNet follows conventional OFDM architecture but uses two DNNs for CE and SD to further improve the performance of the modules. Based on simulation results,

ComNet has better performance than the traditional MMSE-based methods and converges faster since only fewer parameters need to be trained compared with the FC-DNN OFDM receiver [17]. Furthermore, explicit CE helps for channel analysis and CSI feedback in downlink transmission, especially in massive MIMO OFDM systems. The abovementioned advantages make ComNet a competitive candidate for practical system implementation. More research in this topic can be also found in [22], [23].

Although the abovementioned AI-aided methods work well based on simulation, the performance over the air (OTA) in practical environments remains unknown. The state-of-art OTA researches usually train the well designed AI network offline and deploy them on software-defined-radios (SDRs), such as universal software radio peripheral (USRP) for online use [4], [8]. In this case, the trained parameters of the DNNs remain same as they are deployed. Therefore, all possible effects of practical environments have to be considered during the architecture design and training phase, which is impractical in most application circumstances. In [24] a method, named error correcting codes (ECCs), has been proposed to construct labeled datasets at the receiver side so that the trained AI communication systems can be finetuned by transfer learning at run time. This method requires the channel to be changed slower than updating parameters. To the best of authors' knowledge, there has been no report about using AI-aided OFDM receivers in real environments by a real-time video transmission.

In this paper, we compare the FC-DNN OFDM receiver [17] and the ComNet OFDM receiver [21] through OTA test since many details may be ignored in simulation. To address this problem, we develop an online learning architecture, called SwitchNet receiver, which can be trained with offline data as well as real-time online data, to catch some channel features ignored during offline training. Moreover, we set up a real-time video tranmission system based on the two AI receivers for OTA test by utilizing a 5G rapid prototyping (RaPro) system in [25], [26]. The OTA test in diverse environments demonstrates that the AI-aided OFDM receivers are feasible and extendable in practical application, which verifies their potential values for future use.

The rest of this paper is organized as follows. Section II demonstrates the architectures of the FC-DNN receiver, ComNet receiver, and the SwitchNet. Simulation results are demonstrated and discussed in Section III. In Section IV we analyze OTA test results. Finally, we summerize the challenges in future work in Section V.

II. ARCHITECTURES OF AI-AIDED OFDM RECEIVERS

In this section, the traditional and AI-aided OFDM system is introduced first. Then two architectures of AI-aided OFDM receivers are presented in detail. After introducing the existing data-driven FC-DNN receiver [17] and the model-driven ComNet receiver [21], we analyse their drawbacks on practical deployment. and propose SwitchNet to facilitate OTA test and practical application of AI-aided OFDM receiver.

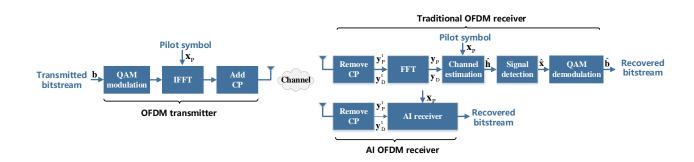


Fig. 1. Block diagram of OFDM system including transmitter, channel and receiver. Pilot symbol inserting at the transmitter and the receiver is to acquire CSI. Compared with traditional OFDM receiver, the AI receiver replaces the latter three modules to map the received symbols into bits directly.

A. Traditional and AI-aided OFDM system

Fig. 1 shows the block diagram of OFDM system including transmitter, channel, and receiver. Two types of OFDM receiver are introduced, including traditional OFDM receiver and AI-aided OFDM receiver. Before the OFDM receiver block is elaborated, the transmitter block and channel model should be introduced first. It is assumed that the ith data block is the signal of interest. For the transmitter, the input bits b are modulated as the transmit symbols. The modulation mode is M-QAM, such as 4-QAM and 16-QAM. Then the serial data is conversed to parallel data for the IFFT block, where an N-point IFFT is performed to generate an OFDM block. After that, a CP is inserted to mitigate the inter-symbol interference (ISI). Finally, the parallel data, x, is converted to serial data and is transmitted into a wireless channel with additive white Gaussian

noise (AWGN), w, which has independent, zero-mean components and σ_w^2 -variance. A sample-spaced multipath channel described by complex random variables $\{h_l\}_{l=0}^{L-1}$ is considered. The delay spread of L-1 samples, resulting in ISI and inter-carrier interference (ICI), is assumed to be shorter than the length of the length of CP P, namely L-1 < P. It should be also noted that the receiver synchronizes with the first path (l=0). In order to learn CSI, the pilot symbols are inserted in the first OFDM block in a frame while the transmitted data is appended in the following OFDM blocks of the frame. The channel is assumed to be constant during one frame, but change from one to another.

At the receiver, the CP is removed and FFT is performed first. Then channel estimation, signal detection, and QAM demodulation are performed. The received pilot and data signals for each subcarrier, $y_P(k)$ and $y_D(k)$, can be expressed as

$$y_P(k) = x_P(k) \otimes h(k) + w(k),$$

and

$$y_D(k) = x_D(k) \otimes h(k) + w(k),$$

respectively, where \otimes represents the circular convolution while $x_P(k)$ and $x_D(k)$ denote the pilot symbols and transmit symbols, respectively.

In contrast, the AI receiver replaces the latter three modules in the traditional receiver as in Fig. 1, which directly maps the received symbols into bits. In the following, two types of AI receivers, i.e., the data-driven FC-DNN and the model-driven ComNet and SwitchNet are described in detail.

B. FC-DNN receiver

A data-driven AI-aided FC-DNN receiver has been proposed in [17], which is different from the traditional OFDM receiver that first acquires CSI explicitly by CE module and then recover the transmitted symbols by signal detection module.

As shown in Fig. 2, the received signals, including pilot and data, are reshaped as the input from complex value to real value initially. Then, the input data goes through three hidden layers. The numbers of neutrons are 500, 250, 120, respectively. In order to acquire high precision of estimated symbols, the output layer is only composed of N/8 neutrons. All but the output of layers use ReLU function, $f_{Re}(a) = \max(0, a)$, as the activation function. The activation function

of output layer is logistic sigmoid function, $f_{Si}(a) = \frac{1}{1+e^{-a}}$, which is beneficial for classifying. The logistic sigmoid function at the output layer maps the input to the interval, [0,1], which can be regarded as soft decisions. Based on soft decisions, hard decisions can be obtained. It should be noticed that 8 identical DNNs with different coefficients are concatenated to recover all transmit bits.

The FC-DNN receiver regards channel estimation, signal detection, and OFDM modulation as one black box and exploits offline training but online deployment method. In training stage, the transmit bits are generated randomly as a label and are modulated to form a frame by inserting pilot symbols. The CSI is simulated by specific channel model and varies with each frame. The ℓ_2 loss and the adaptive moment estimator (Adam) optimizer [27] are used in the training process. At the online stage, the trained parameters are deployed directly to implement bit recovery. The novelty of FC-DNN is that the receiver utilizes an end-to-end structure to realize the global optimization of the receiver, which makes it robust to nonlinear distortions and potentially hardware imperfections, such as no CP and clipping. However, the FC-DNN requires a huge labelled data set to train its weights and converges slowly since a large number of weights need to be trained.

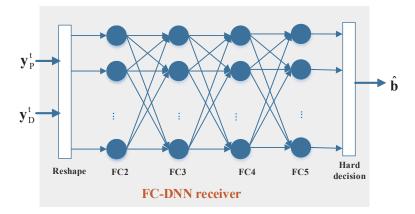


Fig. 2. The structure of FC-DNN. The FC-DNN receiver contains five fully connected layers which maps the received signal to recovered bitstreams directly.

C. ComNet receiver

To alleviate the demand on vast training data and enable the acquisition of CSI, a model-driven AI-aided ComNet receiver has been proposed in [21]. The basic idea of the ComNet receiver

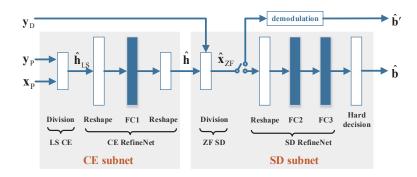


Fig. 3. ComNet receiver architecture. The two subnets use traditional communication solutions as initializations, and apply DL networks to refine the coarse inputs. The dotted short-path provides a relatively robust candidate of the binary symbols recovery.

[21] is to use DNN as auxiliary blocks to refine the original modules in the OFDM receiver in Fig. 1. Fig. 3 illustrates the architecture of the ComNet receiver [21]. Overall, the ComNet receiver [21] adopts two cascaded DNN-based subnets, including the channel CE and SD subnet. In the CE subnet, the LS CE, $\hat{\mathbf{h}}_{LS}$, is first calculated by the element-wise division as following

$$\hat{h}_{\rm LS}(k) = \frac{y_{\rm P}(k)}{x_{\rm P}(k)},\tag{1}$$

where $x_P(k)$, the k-th element of \mathbf{x}_P , and $y_P(k)$, the k-th element of \mathbf{y}_P , are the pilot symbol and the corresponding received symbol at the k-th subcarrier. Then $\hat{\mathbf{h}}_{LS}$ initializes the CE RefineNet to generate accurate CE $\hat{\mathbf{h}}$ through an one-layer DNN. In the SD subnet, the zero-forcing (ZF) SD is first obtained by the element-wise division as

$$\hat{x}_{\rm ZF}(k) = \frac{y_{\rm D}(k)}{\hat{h}(k)}.\tag{2}$$

The $\hat{\mathbf{x}}_{ZF} = (\hat{\mathbf{x}}_{ZF}(1), \dots, \hat{\mathbf{x}}_{ZF}(n), \dots, \hat{\mathbf{x}}_{ZF}(N))$ is then used by the SD RefineNet to predict the distribution of binary data from specified subcarriers, where the SD RefineNet is mainly constituted by three fully connected (FC) layers. The hidden layer FC2 in Fig. 3 uses the ReLU activation function whereas the output layer FC3 uses the logistic sigmoid function. Finally, hard decision is made to decide the bits as 0 or 1. As an alternative way, a short-path of conventional QAM demodulation module can be added to get robust bitstream depending on the scenario.

As the FC-DNN receiver in [17], the ComNet receiver [21] also employs offline training but online deployment method. Different from the end-to-end training of the FC-DNN receiver [17], the ComNet receiver [21] adopts a two-stage training, where the CE subnet and SD subnet are

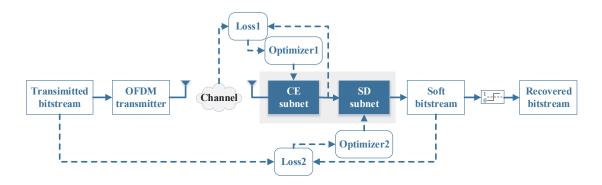


Fig. 4. ComNet receiver two-stage training process. The CE subnet is trained firstly. Sequentially, SD subnet are trained while the trained parameters of CE subnet remain unchanged.

trained separately and successively as shown in Fig. 4. Once the training process of the CE subnet is done, the parameters in the CE subnet will be fixed and invariant in the following training process of the SD subnet. The labels of training data include randomly generated transmitted bitstreams for updating the SD subnet and the specific channel model for updating the CE subnet. To train the CE subnet, the multiplicative parameters are initialized by the real-valued LMMSE CE weight matrix, and Loss1 in Fig. 4 is calculated by the mean-squared error (MSE) between channel labels and the output of CE subnet. Similarly, the MSE between the bitstreams labels and the output of SD subnet is regarded as Loss2 in Fig. 4. Besides, the Adam optimizer [27] is employed in both Optimizer1 and Optimizer2 in Fig. 4.

The novelty of the ComNet receiver [21] is that it introduces the expert knowledge into wireless communications and breaks the black box of pure data-driven AI receiver in [17]. The ComNet provides a general architecture to enable the combination of the DNN networks and the traditional communication blocks and the DNN networks can be replaced by other forms with regard to specific cases, such as using the bi-directional long short-term memory (Bi-LSTM) network [28] under the CP removal case in [21].

D. SwitchNet receiver

In the abovementioned FC-DNN receiver and ComNet receiver, DNN networks are both trained with simulated data offline, which will lead to mismatch and performance degradation if practical channels are different from simulated ones or some distortions are ignored during offline training.

The delay spread is an important parameter to calculate the LMMSE weight matrix in the CE subnet. Two different channel delay environment, such as short channel and long channel, need

two different CE subnets to obtain accurate CSI. An adaptive and practical AI-aided OFDM receiver needs to be established. In addition, to design a practical AI-aided OFDM receiver, online transmission data should be considered into the training process of DNN networks in OFDM receivers. However, we cannot obtain enough data with varying channel because the real channel changes very slowly compared to the simulation. If there are many training parameters in the DNN Network, overfitting will appear.

To resolve above problems, we propose a SwitchNet receiver both using offline data and online data. The SwitchNet receiver is on basis of the ComNet receiver. The difference between them is the architecture of CE subnet. Fig. 5 shows the CE subnet of SwitchNet receiver, which consists of LS CE, two CE RefineNets and an online training parameter α whose value is set as 0 or 1. The structures of the LS CE and each CE RefineNet are the same as those in ComNet receiver. For simplicity, we consider two channel models, including the short channel and the long channel. However, the architecture can be extended to more channel models. As depicted in Fig. 5, the CE RefineNet 1 is a basic neural network for channel estimation and the CE RefineNet 2 is the compensating network of the CE RefineNet 1 in order to adapt different channel environment.

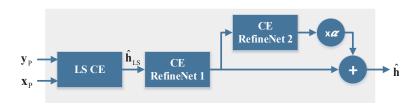


Fig. 5. The CE subnet architecture of SwitchNet receiver. The CE RefineNet 1 is the basic DNN network for CE and the CE RefineNet 2 is the compensating network of the CE RefineNet 1. α is the switch parameter to decide whether the CE RefineNet 2 is accessed or not.

Specially, the two CE RefineNets are trained offline for the two channel models and the switch parameter α is trainable online to decide whether the CE RefineNet 2 is accessed. Due to only one training parameters α , a small batch of OFDM symbols with bit labels can be used and overfitting can be avoided. In the offline stage, the CE RefineNet 1 is trained for the specific short channel firstly. Secondly, the trained parameters of CE RefineNet1 remain unchanged and the CE RefineNet 2 is trained to adapt the long channel. In the online stage, the parameter α is trained to switch to the specific channel. Under the short channel, α is trained as 0 and only CE

RefineNet 1 is accessed. If the channel is long, α will be trained as 1, which indicates the CE RefineNet 1 and the CE RefineNet 2 are cascaded together. Therefore, the estimation channel $\hat{\mathbf{h}}$ is expressed as

$$\hat{\mathbf{h}} = (\alpha \mathbf{W}_2 + \mathbf{I})(\mathbf{W}_1 \mathbf{H}_{ls} + \mathbf{B}_1) + \alpha \mathbf{B}_2 \tag{3}$$

where W_1 is a 128×128 real matrix and B_1 is a 128×1 vector, which are offline trained multiplicative and additive parameters of the CE RefineNet 1, respectively. In addition, W_2 and B_2 are offline trained multiplicative and additive parameters of the CE RefineNet 2 whose dimensions are consistent with the CE RefineNet 1. I is an identity matrix denoting the cascade of CE RefineNet 1 and CE RefineNet 2.

The SwitchNet receiver introduces the idea of online training and has the capability of adjusting to different channel environments, which renders the OFDM system more robust compared with the FC-DNN and ComNet receivers.

III. SIMULATIONS AND DISCUSSIONS

In this section, the simulated performance and the corresponding discussions of the AI-aided OFDM receivers in Section II are presented. Then, the pros and cons of the existing AI-aided OFDM receivers are discussed.

A. Configurations of the simulation system

- 1) Frame Structure: Fig. 6 illustrates the frame structure of the simulated OFDM system. From Fig. 6, each frame contains one pilot OFDM symbol and one data OFDM symbol. Similar to [29] and [11], each OFDM symbol contains 128 samples, where 64 samples are used for pilot symbols or data symbols transmission and others are for guard band and direct current (DC) offset.
- 2) Channel conditions: The short channel and long channel models [11] are used for training and testing the AI-aided OFDM receivers. Additionally, the assumed channel model named theoratical channel is used to generate initialization values of parameters in CE subnet.

Short channel in the simulation is with the exponential (EXP) power delay profile (PDP) defined in IEEE 802.11b to model the indoor channel at the carrier frequency of 2.4GHz [11]. The PDP follows

$$P(\tau) = \frac{1}{\tau_{rms}} e^{-\tau/\tau_{rms}},\tag{4}$$

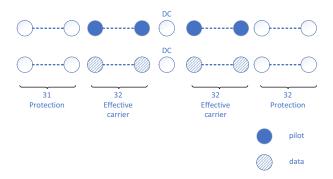


Fig. 6. The frame structure of the simulated OFDM system. A frame contains one pilot OFDM symbol and one data OFDM symbol, and each OFDM symbol contains 128 samples of pilot or data. There are 64 samples are used for pilot symbols or data symbols transmission, while others are for guard band and DC offset.

where $P(\tau)$ is the received power at delay τ , and τ_{rms} denotes the root-mean-square (RMS) delay spread. To generate the short channel, the output of finite impulse response (FIR) filter is used to represent channel impulse response h. Each tap is modeled as an independent complex Gaussian random variable and set at integer multiples of the sampling periods. The maximum number of paths is decided by τ_{rms} and sampling period T_s . In this article, τ_{rms} is set as $0.3 \sim 0.7$ samples, which means the max delay is set as $3 \sim 7$ samples for this EXP environment.

Long channel uses the Stanford University Interim (SUI) channel model [11]. In IEEE 802.16, the suburban path loss environment can be divided into three terrains according to the tree density and path-loss condition, namely the SUI channel model. It can be described by different combinations of channel parameters , where SUI-5 channel model is chosen for use. Its delay spread is $\begin{bmatrix} 0 & 0.4n_{max} & n_{max} \end{bmatrix}$ and power profile is $\begin{bmatrix} 0 & dB & -5 & dB & -10 & dB \end{bmatrix}$, where

$$n_{max} = \left\lceil \frac{10\tau_{rms}}{T_s} \right\rceil. \tag{5}$$

The max delay is set as $8 \sim 14$ samples for this SUI-5 environment.

Theoratical channel is used to obtain initialization values of the LMMSE CE weight matrix $\tilde{\mathbf{W}}_{\mathrm{LMMSE}}$ in the Equation (4) in [29]. It assumes that it obeys multipath fading and its PDP is with exponential distribution. Therefore, the element in the channel autocorrelation matrix [29] can be expressed as

$$R_f(k)/R_f(0) = \frac{e^{-j2\pi\tau_0 k/N}}{1 + j2\pi\tau_{rms} k/N},$$
(6)

where k denotes the lag, τ_{μ} denotes mean delay, $\tau_{0} = \tau_{\mu} - \tau_{rms}$, and N is the size of the discrete Fourier transform (DFT) used in OFDM modulation.

3) Parameters setting: The detailed network layouts of AI-aided OFDM receivers are summarized as TABLE I. Training parameters are shown in TABLE II. The parameters in the AI-aided OFDM receivers need to be trained through labeled data in advance. TABLE II presents the choice of training parameters in simulations.

TABLE I. Network Layouts of AI-aided OFDM Receivers. In this table, network configurations and activation functions of FC-DNN, ComNet and SwitchNet receiver are summarized.

	<u> </u>	Lover	Output	Activation
		Layer	Output	
			dimensions	function
		Input	256	None
		FC	500	ReLU
FC-DNN		FC	250	ReLU
		FC	120	ReLU
		FC	16	Sigmoid
	CE	LS Estimation	128	/
	CE	FC	128	None
ComNet	SD	ZF Detection	128	/
		FC	120	ReLU
		FC	16	Sigmoid
		LS Estimation	128	/
	CE	FC1	128	None
		FC2	128	None
SwitchNet		FC1 out + FC2 out	128	/
		ZF Detection	128	/
	SD	FC	120	ReLU
		FC	16	Sigmoid

TABLE II. Training parameters in simulations.

Parameter	Value
SNR	25 dB
Loss function	MSE
Epoch	2000
Initial learning rate	0.001
Optimizer	Adam

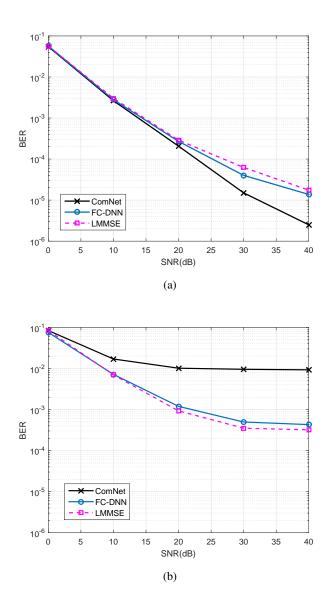


Fig. 7. BER performance of FC-DNN and ComNet under matched channels and mismatched channels. (a) The FC-DNN and ComNet receivers are trained and tested under matched channels. (b) The FC-DNN and ComNet receivers are trained and tested under mismatched channels.

B. Performance of existing AI-aided OFDM receivers

The existing AI-aided OFDM receivers, including the FC-DNN and ComNet, adopt the offline training but online deployment scheme. Since the training process relies on the channel models, the mismatch may occur when the online training channel and the offline testing channel are different. In this case, we evaluate the performance variation of FC-DNN and ComNet when they encounter mismatched channels. The traditional LMMSE channel estimation followed by

MMSE detection method, marked as LMMSE legend, is regarded as the baseline.

Fig. 7 (a) compares the BER performance of ComNet and FC-DNN trained and tested both in EXP channel, which means the trained channel and the tested channel are matched. In general, the ComNet receiver achieves the best performance, followed by the FC-DNN receiver and the traditional LMMSE method. From Fig. 7, these three receivers show similar BER performance within 20 dB SNR since the data for AI-aided OFDM receivers training are inaccurate and affected by noises when the noise power is high. With the increase of SNR, the superiority of the AI-aided OFDM receivers becomes obvious. Even if the FC-DNN just has a small gap compared with the LMMSE method, the ComNet has almost 10-fold BER gain compared with the LMMSE method when SNR = 40 dB. The small performance gain of FC-DNN over LMMSE implies that the DNN network can dig out a bit more information inside the data compared with tradition LMMSE algorithm. The evident performance gain of ComNet over FC-DNN suggests that the expert knowledge of tradional algorithm can be benificial to the learning process of DL networks.

Fig. 7 (b) compares the BER performance of ComNet and FC-DNN tested in the SUI-5 channel different from the trained EXP channel. From the figure, the channel mismatch leads to a BER performance flip, which means the baseline LMMSE becomes the best while the ComNet degrades to the worst. Although the FC-DNN and ComNet are both AI-aided methods, their tolerance toward channel mismatch is totally different. The BER performance of the FC-DNN receiver is still close to LMMSE, wheares the ComNet receiver does not work and becomes saturated when SNR > 20 dB. With the fantastic performance under matched channels and the unusable performance under mismatched channels of the ComNet receiver taken into account, the ComNet receiver seems to be apt to overfit to the trained channel model, which can generate extreme accurate channel estimation of the trained channel, but it is not robust to the untrained channel model. By contrast, the FC-DNN is more robust than ComNet towards channel mismatch, which may result from the redundant network parameters, while it also suffers from the performance degredation. This suggests that even though the existing AI-aided OFDM receivers outperform the traditional method for matched channels, they cannot deal with mismatched channel effectively.

The performance degradation of the existing AI receivers for mismatched channels is due to their totally offline training mode, which makes them only known to the trained channel and "unfamiliar" with the untrained channels. For the AI receivers under real scenarios with

the channels untrained offline, the performance may not be guaranteed. In order to address the channel mismatch issue, it is necessary to train the AI receiver under more channel models offline or train the receiver online to adapt to the environment, as in the proposed SwitchNet. The explicit online training solution to overcome the channel mismatched issue and the corresponding performance of SwitchNet are as following.

C. Performance of SwitchNet receiver

The feasibility of online training and the robustness of the SwitchNet receiver will be demonstrated in this section. To conduct the online training process, we collect 5,000 OFDM symbols of training sequences under Exp and SUI-5 channel models, respectively. Training sequences are inserted into data symbols while transmitting such that the receiver can use the label bits to train the parameter α . In online training stage, 50 OFDM symbols are randomly chosen from training sequences as an epoch and the learning rate is set as 0.006.

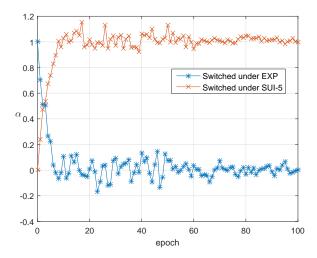


Fig. 8. Online training process when channel changes. The solid curve is the training process of α when channel changes from SUI-5 to EXP. The dotted curve is the training process of α when channel changes from EXP to SUI-5.

Before training online, the receiver works in the specific channel environment. The value of α is 0 when the simulated environment is Exp or α is 1 when the environment is SUI-5. When the channel suddenly changes, the value of α needs adjusting immediately to match the new channel. Fig. 8 shows online-training process when channel changes. We can observe from the Fig. 8 that the value of α of dotted curve changes quickly from 1 to 0 within 10 epochs when the channel

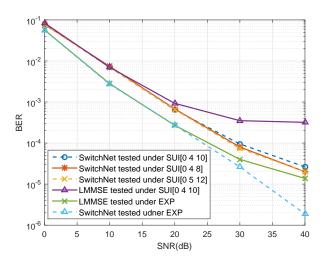


Fig. 9. The BER performance of SwitchNet after online training when channel changes. The SwitchNet receiver switching to SUI-5 still works well when the delay profile at [0 4 10], [0 4 8] and [0 5 12] samples.

changes from SUI-5 to EXP. Similarly, the solid curve adapts to 0 from 1 within 10 epochs when the channel changes from EXP to SUI-5. Within 10 epochs, α gets close to the value of 0 or 1 and oscillates around them. Then the amplitude of oscillation decreases gradually and converges eventually, the reason of which is that the learning rate of Adam optimizer becomes smaller with the increase of training time. Therefore, the online system can perform well in adaptability and stability. In our simulation system, the sampling rate is 300,000 SPS and a frame that includes 20 OFDM symbols has 6000 samples. From Fig. 8, 10 epochs are needed switching to the target channel and each epoch consists of 50 OFDM symbols. Consequently, it only costs 0.5 s to complete switching if the data is collected serially. In practice, the data collection is conducted parallelly in training procedure, which always costs much less time.

Fig. 9 shows the BER performance of SwitchNet receiver after online training when channel changes. From the figure, the SwitchNet receiver can match the correct channel and the BER performance is better than LMMSE which represents the approach of LMMSE channel estimation and MMSE signal detection in the channel of SUI or EXP. For EXP channel, the BER performance of LMMSE and SwitchNet is identical when the SNR is lower than 20dB. However, with the increase of SNR, the performance of the SwitchNet is obviously superior to the LMMSE. For SUI channel, when the SNR is lower than 10dB, the BER performance of LMMSE is the same as the one of SwitchNet. However, when the SNR is higher than 10dB,

the performance gap between them is getting larger. The reason for the results lies in that the BER errors result from the noise effect in the low SNR while the BER errors origin from the bias of channel model. We can also observe from Fig. 9 that the SwitchNet receiver works well in SUI channel when the delay profile at $[0\ 4\ 10]$, $[0\ 4\ 8]$ and $[0\ 5\ 12]$ samples, which indicates that the SUI channel is robust to the max delay which is between 8 and 14. However, all results above relies on the accuracy of online training. Only if the online training parameter α switches to a correct value when the environment changes, the performance of the SwitchNet can be guaranteed.

In summary, the online training process in the SwitchNet receiver can combat the performance degradation under the mismatching channel. Compared to training offline, the SwitchNet receiver needs much less training data and is little influenced by slow change of channel over the air. However, there is only one online training parameter, real channels must be considered offline. Otherwise, the performance will not improve by online training.

D. Complexity Analysis

TABLE III. Complexity analysis for SwitchNet and competing methods.

	FLOPs	Activation memory	Parameters	Time
SwitchNet	0.34M	10.50kBytes	0.17M	1.2e-6s
ComNet	0.31M	9.47kBytes	0.16M	1.2e-6s
FC-DNN	4.33M	29.37kBytes	2.29M	1.2e-6s

TABLE. III compares the complexity in terms of the amount of floating-point multiplication-adds (FLOPs), the activation memory consumption, the amount of parameters and the time consumption in one forward propagation to recover the binary bitstream in a frame among three AI-aided OFDM receivers. From TABLE. III, SwitchNet consumes a bit more resources than ComNet, while it still remains at a low complexity compared with FC-DNN. Specifically, SwitchNet needs 0.03 million more FLOPs, 1.03 thousand more bytes activation memory and 0.01 million more parameters than ComNet, while it only costs approximate 1/10 hardware resources compared with FC-DNN. Compared with ComNet, the extra hardware consumption of SwitchNet is reasonable. As an enhanced architecture of ComNet, SwitchNet has an extra CE subnet to adapt to more channel models, which leads to the slightly larger hardware consumption

compared with ComNet. Meanwhile, the running time of these three AI-aided OFDM receivers is comparative due to the paralleled calculation of graphics processing unit (GPU) and the same depth of network.

Overall, the complexity analysis suggests that SwitchNet owns the advantage of adaptability to more channel models with acceptable sacrifice in hardware resource compared with ComNet, and it consumes considerably fewer hardware resources compared with FC-DNN.

IV. OTA TEST AND RESULT DISCUSSIONS

Apart from simulations, researchers have developed several prototyping systems as testbeds to verify the effectiveness and feasibility of proposed algorithms in real environments. These testbeds include FPGA-based prototyping systems, which offer real-time processing and transmission over a wide bandwidth with large antenna arrays, and general purpose processor (GPP)-based prototyping systems, which process baseband signals on software for fast development and verification. To incorporate advantages, in [25], a novel 5G RaPro system was proposed to deploy FPGA-privileged modules on SDR platforms, implement complex algorithms on multi-core GPPs, and connect them through high-speed 10-Gigabit Ethernet interfaces. Such architecture has been proved to be flexible and scalable by deploying a multi-user full-dimension MIMO prototyping system in [25], [26]. In this paper, we setup the world's first real-time testbed for AI-aided OFDM receivers. We use the RaPro system as our testbed to test the OTA performance of FC-DNN, ComNet, and SwitchNet receivers. Various tests are conducted in different scenarios, and the experiment results and analyses are provided to validate the feasibility and flexibility of the system.

A. System Setup

Fig. 10 (a) illustrates the AI-aided OFDM receiver system based on the RaPro architecture. It is composed of two SDR nodes and a multi-core server. OFDM (de)modulation is implemented on SDRs, which contain RF chains that are provided with a unified reference clock and trigger signal by the timing/synchronization module. AI-aided OFDM receivers are implemented on a multi-core server in a Linux environment. The proposed receivers (FC-DNN, ComNet, SwitchNet) can be developed on multi-core GPPs by programming with high-level language, such as C/C++, in conjunction with Intel Math Kernel Library (MKL), which is a highly optimized and commonly used math library for processors.

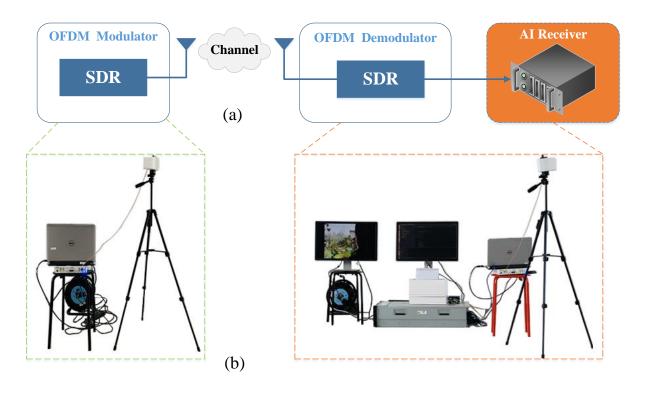


Fig. 10. The AI-aided OFDM receiver system based on the RaPro architecture. OFDM related algorithms are deployed on SDRs while AI receivers are deployed on the multi-core server.

Fig. 10 (b) shows the assembled AI-aided OFDM receiver system. Wireless signals are received by an USRP-RIO through an RF antenna, whose center frequency is adjustable in the range of 1.2 GHz - 6 GHz. After CP removal and FFT-based OFDM demodulation operated by USRP-RIO, the data is sent to the multi-core server via cable. The video stream is recovered by the AI receiver running on the server. To implement the system based on the RaPro architecture, we utilize two SDR nodes of USRP-2943R and a multi-core server that contains 32 Intel Xeon E5-2680 v2 @ 2.8 GHz processors. Each SDR node consists of two RF transceivers of 120MHz bandwidth, from which we can transmit modulated radio signals. The multi-core server provides enough GPPs to meet the requirements of TensorFlow and MKL, which are necessary for the implementation of the AI-aided receivers.

B. Software Implementation

On the transmitter side, the video stream is transmitted through RF module after QPSK modulation and IFFT. On the receiver side, the signals are received by the antenna and performed FFT transformation. Then the data is sent to the multi-core server through user datagram protocol

(UDP) module. The AI-aided OFDM receivers (FC-DNN, ComNet, SwitchNet), running on the multi-core server, will recover the original video stream and display it.

The proposed AI-aided OFDM receivers development process can be divided into two phases, training phase and working phase. The training phase is developed in Python based on Tensor-Flow, relying on the GPUs' powerful computing ability. OTA data captured by USRP-RIO is used to train the weights and biases of the deep neural network via back propagation algorithm. These parameters are stored into csv files after training and provided for the working phase. In the working phase, the forward propagation is implemented in C/C++ with the help of Intel MKL library on multi-core server, with the stored parameters in csv files as the initialization values of the weight matrices and bias vectors. Fig. 11 (a) shows the architecture of the training phase. After the zero padding remove module, 128 effective subcarriers of pilot and data are saved. By separating their real part and imaginary part, 256 real inputs are ready for FC-DNN. And for ComNet, the received pilot divides local pilot to get LS channel estimation. Similarly, the input of ComNet is real form of LS channel estimation and data. Fig. 11 (b) presents the overall data processing program diagram of the forward propagation on the multi-core server. In the multi-core GPP-based AI-aided OFDM receivers design, multi-threading technology is applied to process each module. To avoid the cost of context switching, each processing thread is bounded to a unique central processing unit (CPU) core with semaphore and spinlock as the synchronization mechanism. There are 11 threads in total in the implemented system. The main thread is in charge of scheduling the other threads. A UDP receiving thread is used to collect demodulated data from USRP-RIO. Eight AI detection (FC-DNN, ComNet) threads run in parallel, where the matrix manipulation in forward propagation is realized based on Intel MKL Library. After detection, one UDP sending thread is used to pack the video stream and send to display.

C. Implementation details

1) OTA scenarios for offline trained AI receivers: We choose three different scenarios to test our real-time AI testbed. Scenario 1 is the indoor scenario in Fig. 12 (a), where the transmitter is four meters away from the receiver in the same room with obstacles, windows, and walls around. Scenario 2 is the outdoor scenario in Fig. 12 (b) where the transmitter is at a distance of five meters on a straight road surrounded by several trees. In Scenario 3 as shown in Fig. 12 (c), the transmitter is deployed indoor while the AI receiver is deployed outside the building. These

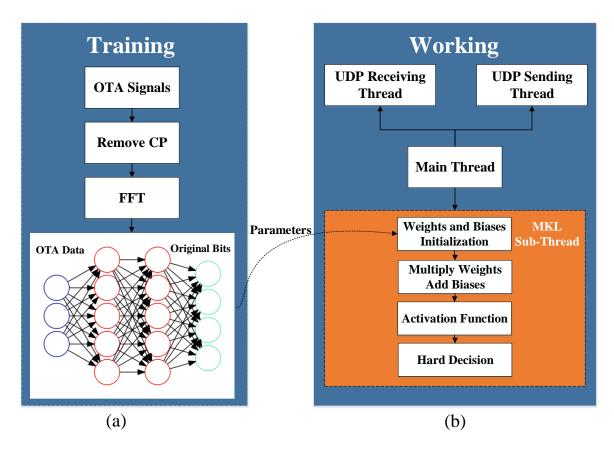


Fig. 11. Over all data processing program of training phase and working phase. The weights and biases of the AI receiver will be trained based on TensorFlow, and will be used to initialize the parameters of the matrices in the working phase.

three scenarios are relatively simple due to limited transmission distance, reflectors, and scatters, and that the corresponding real channels are similar to the EXP channel model. Therefore, we train the FC-DNN and ComNet receiver offline under the EXP channel model to perform the OTA test, under high SNR and low SNR, respectively, by changing antenna gain of the testbed.

2) Training strategy for online training AI receivers: In the real-time system, AI receivers obtain online training dataset by the received training sequence that is sent by the transmitter and known by the receiver. Each bit in the training sequence appears with the probability of one half to keep data balance when training the network. Mean squared error (MSE) is used as the loss function. We use pseudo random coding to generate testing dataset and BER is calculated to measure the online training performance of AI receivers. In [21] the CE subnet is trained independently, which is scarcely possible in online training since the accurate information of the

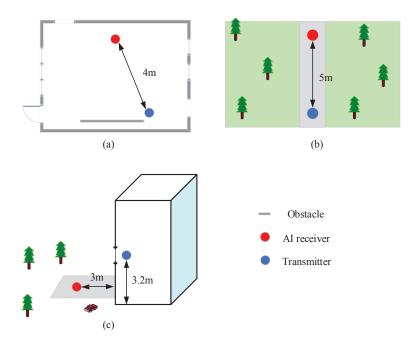


Fig. 12. Three scenarios of OTA test for real-time AI testbed. (a) is the indoor scenario with an obstacle and windows, doors, walls over around. (b) is the outdoor scenario where transmitter and receiver are placed on a straight road surrounded by some trees and grass. (c) is the indoor to outdoor scenario that transmitter is deployed on the second floor of the building and the receiver is outside the building surrounded by several trees and cars.

real channel remains unknown. Thus, the parameters of ComNet are refined by the online training dataset in an end-to-end manner, which is the same as the FC-DNN receiver. The online training method of FC-DNN and ComNet corresponds to the idea of transfer learning. In contrast, the SwitchNet receiver keeps all parameters unchanged expect for α that is trained during the online training phase.

The architecture for online training is shown in Fig. 13. We use the frame structure depicted in Fig. 6, i.e., one pilot symbol followed by one data symbol, for real-time transmission. The data in training sequence are inserted into other data that are used for BER calculation. We call the frame with training data as training frame and that with testing data as testing frame. It takes 0.41 ms to transmit a training frame and a testing frame. We use two data collectors to collect data from these two frames respectively. As long as 50 training frames (i.e., 50 training OFDM symbols) are collected, one epoch of training will be performed with 10 OFDM symbols as the batch size, and the updated parameters will be assigned to the AI-aided OFDM receiver that is

running in the real-time system.

The time for training an epoch is shorter than 0.41ms since we use a server with 36 CPU cores to offer efficient computing power so that each group of 50 training OFDM symbols can be reused to train n epochs before the next group of training symbols is received, where n is designed according to the changing rate of real channel and processing speed of the hardware resources. We set n as 2 in the following online training experiments in Section IV-E. After n epochs the training process pauses until the data collector receive another 50 training frames so that the time variation of the real channel can be tracked. For each receiver, we all collect 5,000 OFDM symbols for online training.

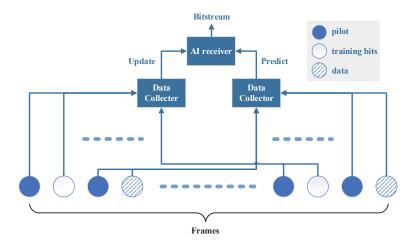


Fig. 13. The online training architecture of AI receivers

D. OTA performance of offline trained AI receivers

In this subsection, we compare the performance of the offline trained FC-DNN and ComNet receivers in OTA tests.

The two receivers are trained offline under the EXP channel model since it is more similar to the abovementioned three test scenarios mentioned in Section IV-C than SUI-5 channel model. The conventional LMMSE method is used as the baseline. As can be seen from Table. IV, the LMMSE method achieves better BER performance than the two AI-aided OFDM receivers in all scenarios, and the FC-DNN receiver slightly outperforms the ComNet receiver.

The main reason is that the three OTA scenarios have limited transmission distances and obstacles, which lead to simple channel realizations. We establish a 2-ray channel model that consists of two paths with the unvaried power proportion and random phase, which is a subset

TABLE IV. BER performance of AI receivers and the LMMSE receiver in OTA test

	SNR	LMMSE	FC-DNN	ComNet
Scenario 1	High SNR	1.74e-6	5.21e-6	5.21e-6
Scenario i	Low SNR	1.88e-4	3.68e-4	3.94e-4
Cooperio 2	High SNR	5.99e-5	1.10e-4	1.11e-4
Scenario 2	Low SNR	4.71e-6	7.36e-4	7.73e-4
Scenario 3	High SNR	2.78e-5	5.82e-5	7.52e-5
	Low SNR	1.30e-5	2.86e-5	5.29e-5

of the EXP channel, to simulate the real channel and the test results show that the LMMSE, FC-DNN and ComNet receivers have similar simulation performance as in the OTA test. The AI-aided OFDM receivers may not show their advantages in the abovementioned simple real channels since they are designed to deal with nonlinear and complex channel conditions by using nonlinear functions.

To verify this discovery, we remove the nonlinear ReLU activation function of the SD subnet of the ComNet, which is called linear SD in the rest of the paper, and test its OTA performance in the same three scenarios. Table V shows that the ComNet with linear SD outperforms that with the original nonlinear SD and is better than the LMMSE method. The OTA results above indicate the superiority and flexibility of a model-driven network to achieve better performance than the conventional methods and a data-driven network in practical implementation by combining communication expert knowledge. In the following online training test, we use the ComNet with linear SD since the OTA scenarios are simple. Notably, it is extendable for SwitchNet to include both linear SD and nonlinear SD by simplying adding one more trainable parameter like α to adapt to both simple and complex channels, and we leave that for future research.

Some effects of imperfections in practical implementions, such as antenna directions, system synchronization error, and difference between real channel and channel models, are not considered during offline training phase. As a result, the offline well-trained AI receivers cannot perform well in real environments due to mismatch, which suggests the necessity to consider possible situations that may occur in implementation during the offline training phase to ensure OTA performance, especially for a data-driven network that relies on training data and combine no expert knowledge.

TABLE V. Impact of the SD subnet in OTA test (shown as BER performance)

	SNR	ComNet-	ComNet-	LMMSE
		linear	nonlinear	
		SD	SD	
Scenario 1	High SNR	8.68e-7	5.21e-6	1.74e-6
	Low SNR	1.90e-4	3.94e-4	1.88e-4
Scenario 2	High SNR	5.47e-5	1.11e-4	5.99e-5
	Low SNR	4.51e-4	7.73e-4	4.71e-6
Scenario 3	High SNR	2.60e-5	7.52e-5	2.78e-5
	Low SNR	1.30e-5	5.29e-5	1.30e-5

E. Online Training for AI receiver

In this subsection, we consider the online training method for the AI-aided OFDM receiver. The network architecture and training strategy are illustrated in Section II-D and IV-C; respectively. We compare the BER performance of SwitchNet under different channel environments in Table.VI and demonstrate that the real channel is more similar to the EXP than the SUI-5 channel model. Therefore, the initialized SwitchNet is trained with the SUI-5 channel to validate the effect of online training when deployed in real channel. The number of labeled data is important for neural network to avoid overfitting. However, in the real-time transmission system, it is difficult to obtain a large number of data as the time for collecting data and training network is limited. Therefore, the network with fewer parameters optimized in online training process will decreed.

TABLE VI. BER performances of three AI receivers trained under matched channel (EXP) and mismatched channel (SUI-5)

	Channel condition	SwitchNet	ComNet	FC-DNN
BER	Mismatched channel	2.0e-2	2.0e-2	1.2e-3
DER	Matched channel	4.4e-4	4.4e-4	8.8e-4

The SwitchNet performed by using offline data to adapt to channel alterations is composed of two CE subnets trained offline and a tunable parameter α is trained online to choose the contribution of the two CE subnets dynamically. To indicate the superiority of the SwitchNet, we also perform transfer learning for ComNet and FC-DNN by using similar architecture in

Fig.13, where the network is retrained by using online data in the transmission stage on the basis of the offline trained network.

TABLE VII. The training process of α when initialized as one under the real channel.

epoch	0	10	20	50	100
α	1.0	0.107	-0.168	-0.065	-0.059

Table. VII shows the change of α in the online training process, where the learning rate of it is optimized. The initialized value of α is set to one as the network is initialized under the SUI-5 channel model and decreases to close to 0 within 20 epochs, which indicates the SwitchNet can adapt to the real channel by online training data. From the value of α after training, the real channel in this OTA testing data is not same with EXP thoroughly because the α is stability at a negative value close to 0 in real data but the absolute value is less than 10e-3 in simulation. The SwitchNet can also show robustness in the channel similar to one of its CE subnets and try to reach the better performance.

TABLE VIII. BER performances of SwitchNet, ComNet and FC-DNN with different number of epochs and optimizaed learning rates.

		SwitchNet	ComNet	FC-DNN
	10	4.7e-4	1.4e-3	7.7e-4
epoch	100	4.5e-4	6.7e-4	6.8e-4

Table. VIII compares the BER performances of the SwitchNet, ComNet and FC-DNN by using online training with different numbers of epochs, and the learning rate for each network is optimized. The ComNet and FC-DNN are trained by transfer learning. We can observe that the SwitchNet can perform online training rapidly with a small number of epochs while ComNet and FC-DNN need relatively a large number of epochs to obtain similar performance. Therefore, the SwitchNet needs less training time and data to adapt the channel alteration by online training.

Furthermore, we also investigate the impacts of the learning rate for three networks. The initialized learning rates for SwitchNet, ComNet and FC-DNN are 0.6, 0.01, 0.01; respectively. The learning rate is decreased 1/5 when each 1/5 of the total epochs have been trained. Table. IX illustrates that the SwitchNet is relatively insensitive to the learning rate. Conversely, the

TABLE IX. BER performances of SwitchNet, ComNet and FC-DNN with different number of epochs and decayed learning rates.

		SwitchNet	ComNet	FC-DNN
epoch	10	7.4e-4	1.1e-2	1.4e-3
	100	4.5e-4	9.8e-3	1.4e-3

ComNet and FC-DNN heavily depend on the learning rate. An improper learning will result in severely deterioration and the performance cannot restore through online training, as well as more training data and time.

From above results, we can conclude that SwitchNet is more promising than ComNet and FC-DNN receivers when considering online training. As only one parameter are required to be optimized in the online training process, the SwitchNet can avoid overfitting and reduce time cost. Furthermore, a little more trainable parameters can be introduced into the network to further improve the flexibility and adaptability, as real-time system have adequate hardware resource and time for training these model-driven AI networks.

V. CONCLUSIONS AND FUTURE CHANLLENGES

In this article, we have proposed an online trainable AI-aided OFDM receiver, named Switch-Net, to adapt to the channel variation and diversity in the OTA sceinarios. The proposed Switch-Net receiver pretrains multiple channels offline and reserves an online trainable parameter to act as a switch that can choose the network for the real transmission. Simulation results indicate that the proposed SwitchNet receiver shows feasibility in online training and outperforms the ComNet receiver and the FC-DNN receiver, as well as the traditional LMMSE-MMSE baseline in terms of the BER performance. For real-world applications, OTA tests have demonstrated BER gains under real scenarios and efficient online training characteristics of the proposed SwitchNet receiver.

Although AI-aided OFDM receivers relieve the difficulty of mathematical modeling and have the potential to outperform conventional communication systems, a performance gap may occur between offline and the OTA test due to the difference between simulation and real environments. It is challenging to consider all possible effects in implementations to collect suitable training dataset and improve robustness of the AI-aided OFDM receivers during offline

training phase. Online training is a promising method to solve this dilemma. Transfer learning is a straightforward idea to refine the AI-aided OFDM receivers according to the OTA data collected during running time. However, the number of parameters to be refined is large and therefore a large amount of online training data is necessary, which needs much time to collect, let alone the slow-varying real channel reduces the diversity of online training dataset. Thus, a better transfer learning strategy that can get enough high-quality training dataset in time should be taken into consideration. SwitchNet offers a realizable online training scheme by sharply reducing the number of parameters to be trained. Its adaptive ability is guaranteed by adding subnets that are offline trained under different channel models, which increases redundancy. A flexible and stable approach that can adapt to real channels more intelligently remains for future research.

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