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Deep Neural Network-Based Receiver for Next-Generation LEO Satellite Communications

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ABSTRACT This paper proposes a novel deep neural network (DNN)-based receiver for next-generation low Earth orbit (LEO) satellite communications. The DNN receiver can concurrently compensate for multiple imperfections of the satellite communication system to improve the quality of satellite-to-ground transmission. A special focus has been placed on handling the nonlinear distortion in the transmitted signal caused by space-borne high-efficiency radio frequency power amplifiers (RF-PAs), which is crucial in high-throughput satellite communications, but has been overlooked by existing relevant research. In this receiver, a DNN is designed and trained to learn the channel effects, nonlinearities of the RF-PAs, and digital modulation schemes in the received signal for demodulation and nonlinearity/channel effect compensation at the same time. The proposed receiver has been evaluated using five popular filtered orthogonal frequency division modulations with the nonlinear distortions experimentally extracted from a real gallium nitride (GaN) RF-PA and the additive white Gaussian noise channel generated by simulations. The validation results demonstrate that the DNN receiver can accommodate different modulation schemes and two typical groups of RF-PA classes with a satisfactory bit error rate performance. It has the potential to boost the performance of existing on-orbit LEO satellite communication systems with minimal system modifications and serves as a promising solution for future satellite communication services.

INDEX TERMS Deep neural network, filtered-OFDM, radio frequency power amplifier, nonlinear distortion, digital signal recovery, demodulation, low Earth orbit satellite communications.

I. INTRODUCTION

With the fifth-generation (5G) communication network being commercialized worldwide, low Earth orbit (LEO) satellite-to-ground communication has become one of the hot topics in both academia and the space industry, due to its attractive advantages (i.e., lower signal attenuation and shorter propagation latency) compared to medium Earth orbit (MEO) and high Earth orbit (HEO) satellite communications [1]. There is no doubt that LEO satellite communications will continue playing as a key role in sixth-generation (6G) communications [1]. Although LEO satellites deployed at 500–1500 km feature a relatively lower signal attenuation than MEO and HEO satellites, the transmitter of the LEO satellite still requires a medium- or high-power RF-PA for magnifying the power of radio signals to support such a long transmission distance with desired data rates. Due to the limited power resources available on the LEO satellites, the space-borne RF-PAs usually work in or close to a saturation region to obtain high power efficiency, leading to significant nonlinearity. This nonlinearity could cause severe distortion in signals with high peak-to-average power ratios (PAPR), for instance, the filtered orthogonal frequency division modulation (f-OFDM) signal. f-OFDM is an advanced and flexible waveform that features low out-of-band radiation while maintaining most of the advantages of conventional OFDM, and has

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become a part of the 5G standard now [2]. On the other hand, the scientific community has made efforts to integrate satellite communications with terrestrial communications over the past few years, especially the physical layer (PHY), and hence, f-OFDM is recommended as the most promising waveform for LEO satellite communications [3]. Therefore, dealing with the nonlinearity of space-borne RF-PA is crucial for achieving broadband connections in next-generation LEO satellite services.

Commonly used approaches to handle the nonlinearity of the RF-PA are digital predistortion (DPD) techniques, for instance, memory polynomial [4] and lookup tables [5]. As shown in Fig. 1a, the DPD techniques predistort the original signals to compensate for the nonlinear distortion caused by the RF-PA. However, the DPD technique has an unacceptable drawback for LEO satellite communications: consuming significant power and computing resources. To overcome this drawback, a power back-off technique is widely applied in LEO satellite communication systems, as shown in Fig. 1b. The power back-off technique decreases the input signal power of the space-borne RF-PA to relax the nonlinearity, leading to poor power efficiency (e.g., 32.6 % in [6]). Therefore, a new technique that can elegantly solve this issue is highly desired for next-generation LEO satellite communications.

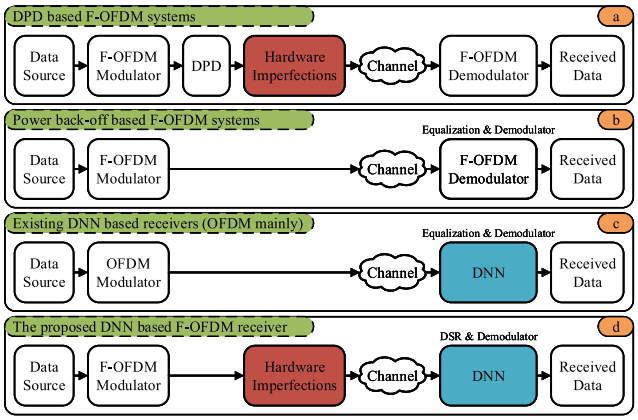

FIGURE 1. System architecture comparison between a) the conventional DPD based f-OFDM system, b) the conventional power back-off based f-OFDM system, c) the existing DNN based receiver overlooking the RF-PA nonlinearity, and d) the proposed DNN based f-OFDM receiver including the RF-PA nonlinearity mitigation.

Currently, several deep learning techniques have been well applied in wireless communications [7], especially in PHY [7]–[13], demonstrating their great potential in communication system characterization and optimization. Generally, the development of deep learning in PHY mainly focuses on enhancing certain models used in wireless communication systems [9]. In [10], deep learning techniques remarkably outperform traditional machine learning techniques such as support vector machines, random forests, and logistic regression in terms of the identification accuracy of different digital modulations. Another more radical research direction is a deep learning-based end-to-end communication system design [9], [11]–[14]. The concept of this design is to jointly optimize the whole communication system within one or more DNNs or even generate a new waveform as a transmitted signal [11]. In this way, traditional rigid mathematical models such as carrier frequency synchronization, channel equalization, modulation and demodulation, and channel coding and decoding can be omitted. Instead, an elaborately customized communication system is designed for the specific communication environment with the optimal transmission performance. Generally, these techniques can achieve a better bit error rate (BER) performance in low signal-to-noise ratios (SNRs) than traditional communication systems. The existing deep learning-based receivers have focused on different technical aspects in the communication channel, such as multipath fading channels, flat fading channels, and MIMO channels. The nonlinearities of RF-PAs to date, however, have been overlooked in the existing end-to-end solutions, as shown in Fig. 1c [9]. Additionally, the existing DNN-based methods were verified using basic waveforms (e.g., PSK, QAM, and OFDM signals) [9], [13], [14] or new waves [11], [12] and cannot be easily implemented in modern communication systems, which favor advanced waveforms such as f-OFDM.

In this paper, a new DNN-based f-OFDM receiver is proposed to overcome this challenge. As shown in Fig. 1d, the proposed system architecture is in line with the end-to-end communication system design. The novelty of the proposed receiver is the use of one DNN model to compensate for the nonlinear distortion in the received signal caused by the space-borne RF-PA at the ground station and to apply demodulation simultaneously. After the DNN deployed at the ground station learns the imperfections of the communication environment and modulation types, the space-borne RF-PA is allowed to operate in its saturation region for signals with advanced modulation schemes, while maintaining the expected BER performance. This helps the LEO satellite to operate with high power efficiency. In addition, experimental results show that the proposed technique could accommodate different nonlinearities of the RF-PA and modulation types by training different DNN models. As no modifications in transmitting are required on satellites, the proposed system has the ability to enhance satellite-to-ground communication for existing on-orbit LEO satellites. Different from our previous work [6], the proposed work not only compensates for the nonlinear distortion caused by the space-borne RF-PA but also combines the compensation and demodulation within one model. The proposed technique also provides a promising solution for future satellite communications.

II. IMPERFECTIONS OF LEO SATELLITE-TO-GROUND COMMUNICATIONS

Regarding LEO satellite-to-ground communications, the main contributors of imperfections that degrade the transmission quality are channel effects and hardware imperfections.

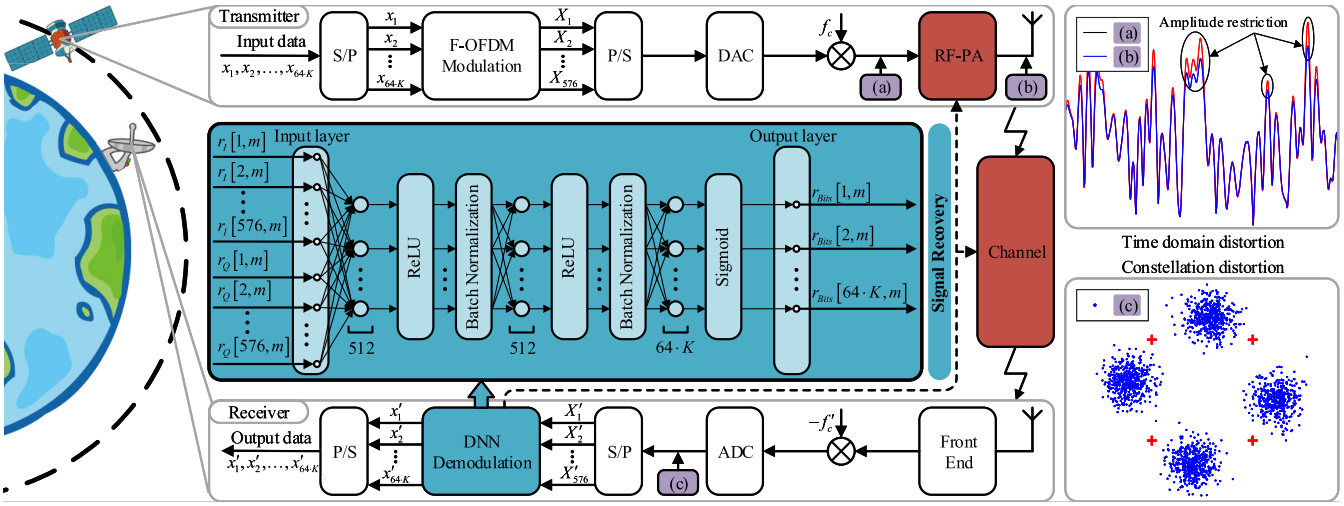

FIGURE 2. Proposed system structure using the DNN and the illustration of the signal distortion caused by the nonlinear space-borne RF-PA.

A. CHANNEL EFFECTS

Because of insignificant multipath fading, the LEO satellite-to-ground communication channel can be modeled as a point-to-point additive white Gaussian noise (AWGN) channel [6], [15]. Moreover, because of the fast motion of LEO satellites, the LEO satellite-to-ground communication channel features a wide and rapid time-varying Doppler frequency shift and received signal power. Technically, the time-varying Doppler frequency shift can be well handled by existing solutions [6]. Additionally, in the recent research [6], it has been shown that the impact of the time-varying received signal power can be eliminated by the batch normalization layer of the DNN. Apart from all of the above, other factors can also affect the received signal, including the atmospheric absorption loss, antenna misalignment loss, and modulation loss caused by imperfect demodulation. However, compared with the time-varying SNR, the effects of these effects are much smaller, especially for S- and X-band LEO satellite-to-ground communication systems. Hence, the channel in this work is only considered as an AWGN channel featuring a time-varying SNR.

B. HARDWARE IMPERFECTIONS

Nonlinear distortion could affect the output signal of the RF-PA in both amplitude and phase. In the time domain, the amplitude of the signal cannot remain equivalently magnified when the instantaneous input power frequently changes, as shown in Fig. 2. In the figure, K represents the digital modulation order. It can be observed from the time domain distortion in the figure that when the instantaneous input signal power of the RF-PA reaches the level that drives the RF-PA into its saturation region, the peak amplitude of the output signal would be evidently restricted. The nonlinear distortion also changes the phase of the signal, leading to a degradation of the BER performance. To observe the phase distortion, QPSK-based f-OFDM modulation is used, as shown in Fig. 2.

In addition, for simplicity, perfect f-OFDM synchronization for other system imperfections, including timing, carrier frequency offsets, and Doppler frequency shift synchronization, has been performed at the receiver.

III. CONSTRUCTION AND DEFINITION OF THE PROPOSED SYSTEM

Different from the existing DNN (i.e., autoencoder)-based end-to-end communication system design, the proposed system makes full use of the domain knowledge of the f-OFDM transmitter. Assuming no extra work is needed on the satellite, a conventional f-OFDM transmitter [16] without the use of any DPD or power back-off techniques is applied in the proposed system. Then, a DNN is introduced in the receiver at the ground station to learn both the modulation type and the nonlinear distortion included in the received signal, as shown in Fig. 2. The received signal (i.e., signal (c) in Fig. 2) is used for training, and the trained DNN can demodulate the received signal within one model without using fast Fourier transform (FFT) operations or digital demodulation schemes after training. In the meantime, this trained DNN also has the ability to compensate for the combined imperfections caused by the space-borne RF-PA and LEO communication channel, which is called signal recovery in Fig. 2.

The proposed system only requires modifications in the receiver without any other operations at the transmitter. Note that it could be better to utilize the structure of the autoencoder (i.e., encoder and decoder at the transmitter and receiver, respectively) to globally optimize the communication system to achieve the optimal transmission performance. However, the global optimization method needs modifications at the transmitter, and hence, the autoencoder cannot be applied in existing on-orbit LEO satellites. In addition, new technologies are usually not stable, such that they could only be carefully tested and verified for future satellite communications. The proposed system not only provides

a promising solution to apply deep learning techniques for future LEO satellite communications but also has the potential to upgrade the existing on-orbit LEO satellite transmission link to achieve a better transmission performance.

The configuration of the tested f-OFDM transmitter in this work is shown in Table 1. Note that considering that f-OFDM is a waveform standard of 5G, a customized f-OFDM signal could be suitable for simulations and BER analysis. Therefore, to ensure that nonlinear distortion is correctly introduced into the signal by the simulations, a 512 subcarrier f-OFDM system with 64 data subcarriers inside is used to verify the proposed receiver. The filter used for side-lobe suppression of the conventional OFDM signal follows ref. [16], but the order of the filter is set to 64 considering the limitation of the space-borne computing resource. Therefore, one f-OFDM signal has 576 complex-number samples. In addition, f-OFDM signals based on different digital modulation schemes feature almost the same PAPR, which is approximately 12.85 dB. For the RF-PA, this work takes into account both class AB and class B working states, which already have strong nonlinearities.

TABLE 1. System configurations.

Modulation type	QPSK, 8PSK, 8QAM, 16QAM, 16APSK					
Subcarriers	512					
Data subcarriers	64					
Filter type	Windowed Sinc [16]					
Window type	Hanning					
Filter length	64					
PAPR	12.85 dB					
RF-PA working state	Class AB			Class B		
V_{DD} (V)	28	20	12	28	20	12
V_{GG} (V)	-2.9	-2.9	-2.9	-2.3	-2.5	-2.7
I_{DQ} (mA)	66.82	61.20	55.63	274.90	201.10	121.00
Channel	AWGN					

IV. TRAINING PROCESS AND NETWORK DEFINITION

The training process of the proposed application is shown in Fig. 3, where the green and blue arrows are the forward and back propagation [6], respectively. The purple arrow shows that the RF-PA is modeled by experiments. In the training process, parameters of the DNN are updated step by step by reducing losses between outputs of the DNN (i.e., predicted values) and true values (i.e., labels). The DNN can gradually learn features hidden in training data for classification or regression missions. Generally, if the DNN is trained as a classification model, the cross-entropy function is a commonly used loss function. On the other hand, the mean squared error (MSE) is typically used to train the DNN to be a regression model.

As seen in Fig. 3, the expected outputs of the DNN are the bits corresponding to the f-OFDM signals fed into the DNN. Therefore, the number of input neurons is correlated with the number of samples of one f-OFDM signal, and the number of output neurons is correlated with the type of the digital modulation scheme and the number of data subcarriers. Due to the complex-number property of the f-OFDM signal, the input samples are divided into two paths represented as r_I and r_Q. Therefore, the number of input and output neurons of the DNN is set to 1152 and $64 \times K$, respectively, where K is the digital modulation order. The DNN has $2^{64 \cdot K}$ possible outputs, and hence, the DNN is difficult to train as a classification model using the cross-entropy loss. In this paper, the MSE loss function is used to train the DNN as a regression model. Note that to reasonably constrain the numerical size of the DNN outputs, a sigmoid active function with the maximum and minimum values of 1 and 0 is employed as the last layer.

Several important settings of the DNN are listed in Table 2. It is worth noting that if the loss no longer decreases after 20 epochs or the adaptive learning rate reaches the minimum learning rate, the training process is stopped immediately. To efficiently capture sufficient features from training data, the learning rate is initially set to 0.01 and reduced while training in a reasonable way. Then, the adaptive moment estimation (Adam) method is used as an optimizer for updating the parameters of the DNN, considering its high efficient computation [17]. In addition, considering the point-to-point AWGN channel, an AWGN with an approximate SNR is added on the transmitted signal for improving the noise robustness of the DNN [6]. In this work, the training SNR is chosen when the theoretical BER of the specific digital modulation scheme reaches 10^{-5}, as shown in Table 2.

TABLE 2. Configurations for training.

Maximum epochs	200				
Step/epoch	50				
Batch size	5000 Filtered-OFDM signals				
Early stop patient	20 epochs				
Initial learning rate	0.01				
Minimum learning rate	10^{-5}				
Loss function	Mean squared error (MSE)				
Optimizer	Adam				
Modulation type	QPSK	8PSK	8QAM	16QAM	16APSK
Training SNR	12.6 dB	17.8 dB	17.3 dB	19.4 dB	20.5 dB
Training bits/step	$5000 \times 64 \times K$				
Testing bits	$100000 \times 64 \times K$				

All operations are realized using Python 3.8.4 on Visual Studio Code, including the f-OFDM signal generation, nonlinear distortion simulation, and training process. It is worth noting that the nonlinearity is modeled by the memory polynomial method using measured data from a CGH40006P RF-PA, as shown in Fig. 3. The measured data are collected using an R&S SMBV100A signal generator and R&S FSQ26 signal analyzer controlled by MATLAB. The original f-OFDM signals are distorted by feeding them into the memory polynomial model. In addition, the DNN is built and trained using Keras 2.3.0-tf, and the version of Tensorflow is 2.2.0.

V. FEASIBILITY ANALYSIS OF THE PROPOSED SYSTEM

As mentioned in section I, several rigid mathematical models with different functions are developed to support the whole

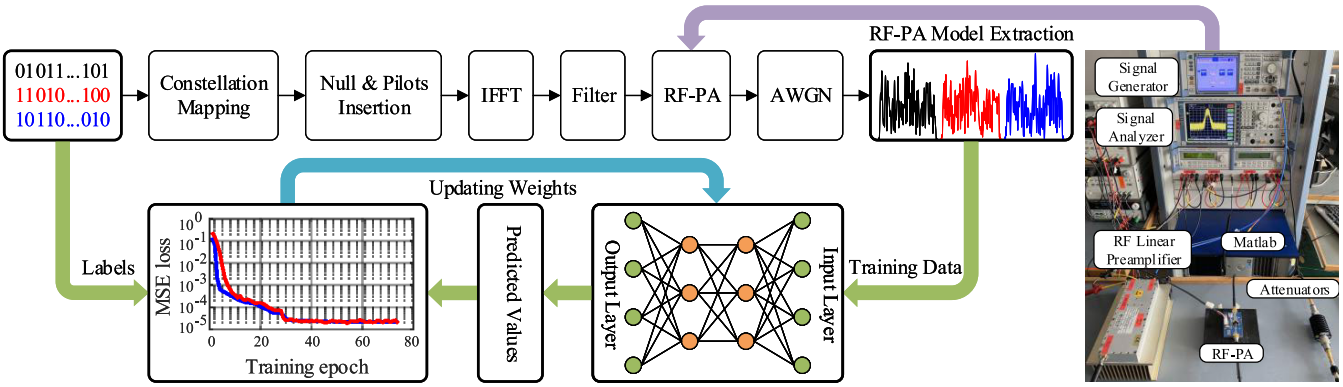

FIGURE 3. Diagram of the training process and the experimental scene for extracting characteristics of the RF-PA.

conventional communication system. The OFDM demodulation (i.e., FFT) and conventional DPD techniques are both mathematical models described by a few coefficients. Note that DPD techniques can be exploited in the receiver to recover the received nonlinear distorted signal under an ideal environment. However, the recovery method is not a workable solution for conventional DPD techniques due to the time-varying received signal power, which is not a challenge for the DNN-based recovery method [6]. The DNN is also a mathematical model with many coefficients and features a fixed connection form. Different from the conventional mathematical model, the DNN is nonlinear due to nonlinear functions (e.g., the ReLu function shown in Fig. 2). Benefiting from this nonlinearity, the DNN can fit arbitrary curves that are also recognized as functions by training. Therefore, the DNN could usually model complex problems that are difficult to express mathematically and even cover all functions within one model. This inference is proved by this work. The DNN not only demodulates the f-OFDM signal but also has the ability to recover the received nonlinear distorted signal. In other words, the DNN could integrate the two mathematical models together into one model and simultaneously handles the time-varying effect.

VI. EXPERIMENTAL RESULTS

To design a power-efficient LEO satellite, the nonlinearity of the space-borne RF-PA must be considered; otherwise, the transmission performance would be degraded. Therefore, a reasonable experiment using QPSK-based f-OFDM modulation under different levels of nonlinear distortion is performed in this work to demonstrate that the nonlinearity of the RF-PA can be overlooked in the training process, as shown in Fig. 4a. Both the amplitude and phase distortions caused by the nonlinearity of the RF-PA lead to a significant increase in the error vector magnitude (EVM). In the simulation, the EVM is used to measure the level of nonlinear distortion. From the figure, the existing conventional DNN-based receiver, which overlooks the nonlinearity in the training process, no longer works using the experimentally extracted RF-PA model corresponding to an EVM of 1055.91 %. If the power back-off technique is adopted to relax the nonlinear distortion caused by the RF-PA, the BER performance of the conventional DNN-based receiver would be improved but still has a gap with the theoretical BER performance bound. Therefore, if nonlinear distortion is not involved in the training data, the DNN would not know the nonlinearity of the RF-PA, and hence, the DNN-based receiver does not work properly.

The proposed DNN-based f-OFDM receiver can accommodate different digital modulation schemes. In this work, QPSK-, 8PSK-, 8QAM-, 16QAM-, and 16APSK-based f-OFDM modulations are verified. QPSK, 8PSK, and 16APSK are commonly employed in LEO satellite communications due to their low PAPR (approximately 4 dB). 8QAM and 16QAM are typical digital modulation schemes in terrestrial communications. It can be seen from the Fig. 4c and Fig. 4d that the BER performance of the proposed receiver using an QPSK based f-OFDM modulation is close to the theoretical BER performance. With the growing modulation order, a slight BER performance degradation is observed due to the increasingly complex and diverse constellations, but the proposed receiver still performs very well with only a 1 dB deviation from the theoretical bound. The phase shift caused by the RF-PA has a more serious impact on complex constellations than on simple constellations. Compared with the existing DNN-based receivers that are trained without nonlinear distortion, a slight degradation of the BER is also seen but within the acceptable range. The nonlinearity of the RF-PA cannot be completely compensated, especially for high-order digital modulation schemes. The maximum SNR degradation in the 16APSK-based f-OFDM modulation is approximately 1 dB when a BER of 10^{-5} is required.

In addition, the proposed receiver can handle different working states of the RF-PA well, as shown in Fig. 4b. Generally, classes AB and B are the most commonly used working states to achieve an optimal trade-off between power efficiency and nonlinearity. The drifting temperatures, jittering supply, bias voltages, and varying input power are all factors that could cause state variations of the RF-PA in real operation. Therefore, it is of the highest importance to validate the

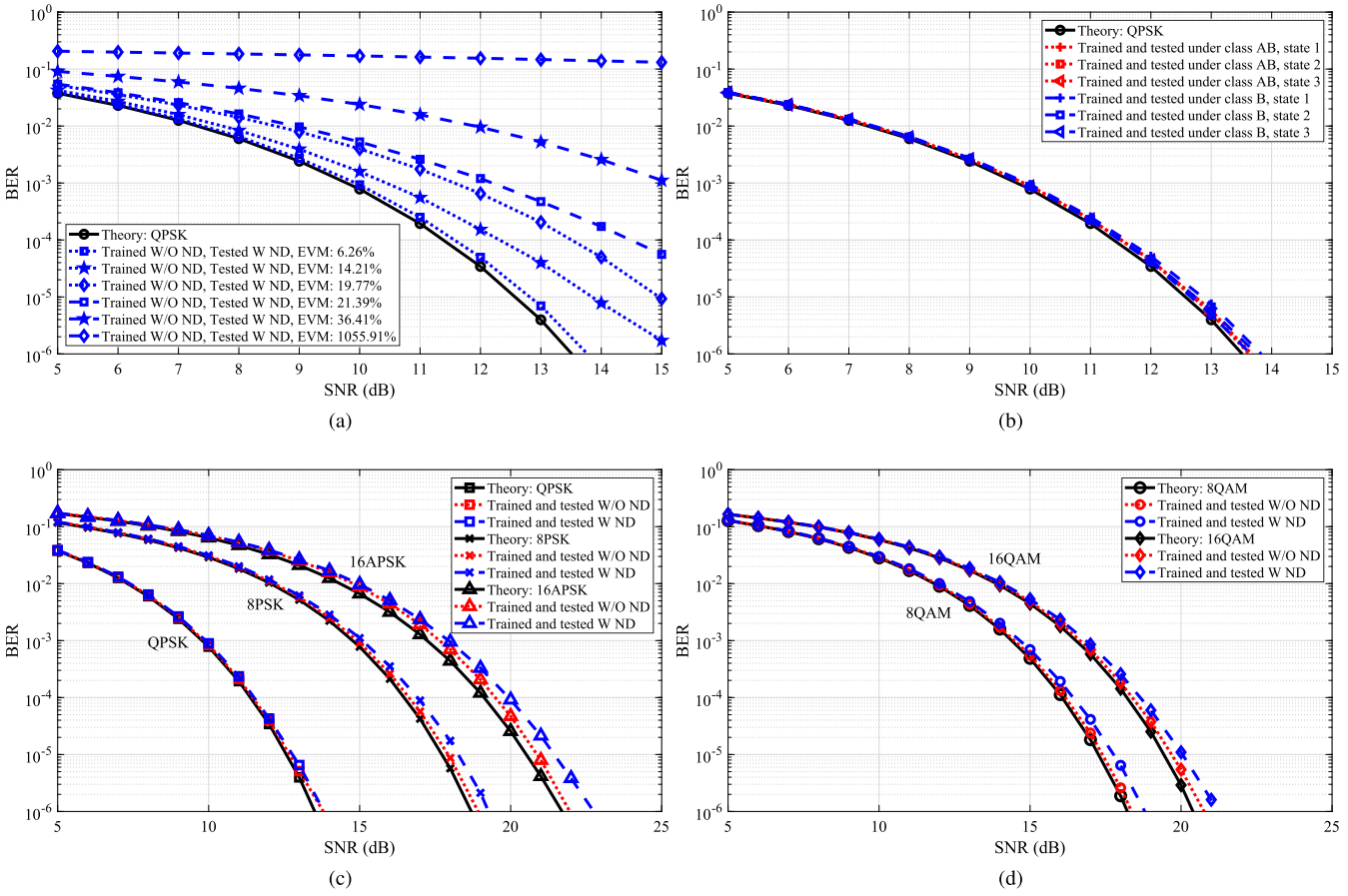

FIGURE 4. Experimental results to show a) the necessity of considering the nonlinear distortion (ND) using the QPSK based f-OFDM modulation with different nonlinearities of the RF-PA measured by the error vector magnitude (EVM) and validate the DNN with b) multiple RF-PA working states, c) commonly used modulations in LEO communications, and d) commonly used modulations in terrestrial communications.

capability of the proposed receiver under different working states of the RF-PA. To eliminate randomness, three different voltage supplies of each class are conducted, represented as state 1, state 2, and state 3. The supply voltage, bias voltage, and quiescent current of each state are shown in Table. 1. For simplicity, the QPSK based f-OFDM modulation is utilized to verify the proposed idea. It is worth noting that a new DNN needs to be trained for fitting the current new working state of the RF-PA. Even so, this experiment can sufficiently prove that the DNN can handle different RF-PAs and different working states of the same RF-PA.

VII. DISCUSSION

When the proposed technique is implemented at the ground station, the computing resource does not prevent the application of this work to satellite-to-ground communications, especially considering the benefit to power efficiency for LEO satellites that this technology can bring. As a potential tool, the DNN-based receiver can also be developed for satellite-to-satellite communications in which power and computing resources are severely limited. The computational requirement consequently needs to be analyzed if that is the case.

In addition, even though the proposed DNN receiver can be used in satellite-to-ground communication for existing on-orbit LEO satellites, it does require an appropriate training dataset from the LEO satellites for training the DNN. One solution is to request the on-orbit satellites to send a known pilot and training sequences in the downlink data. In this way, the imperfections of the whole communication system and modulation types are embedded in the known information (i.e., pilots and training sequences). Then, the DNN can be trained using that information. This method also provides a promising solution to realize real-time online training for handling time-varying communication environment changes such as rain fades. For future LEO satellite communications, a simple way to apply this work is to train the DNN to learn the hardware imperfections and modulation types before the flight. Considering that the LEO satellite-to-ground communication channel can be modeled as a point-to-point AWGN channel, the DNN can still work properly. However, due to space limitations, this work is not included in this paper.

VIII. CONCLUSION AND FUTURE WORK

In this paper, a novel DNN-based f-OFDM receiver is proposed for power-efficient high-throughput LEO satellite communications. Different from the existing DNN-based receiver techniques, which focus mainly on channel effects,

the proposed receiver also takes into account the main hardware imperfections caused by the RF-PA, which is crucial for high-throughput satellites. Experimental validation has been performed to demonstrate the necessity and benefit of including the nonlinear distortion caused by the RF-PA in training. In addition, the proposed DNN-based f-OFDM receiver can perfectly handle different digital modulation schemes and nonlinearities of RF-PAs in different operation classes. By learning the imperfections and modulation types of the communication system, the proposed receiver has the potential to improve the transmission quality of existing on-orbit LEO satellites without any modifications to the satellites. This paper not only provides a new design method for next-generation LEO satellite communications but also shows the potential of this work for terrestrial communication systems, such as 5G or other point-to-point communication networks.

As mentioned in section III, adding an autoencoder could assist communication systems in achieving the optimal transmission performance. If the encoder is introduced in the transmitter to globally compensate for the nonlinearity of the RF-PA, the BER performance of high-order digital modulation schemes may be further improved. Therefore, autoencoders could be a major research direction in future work.

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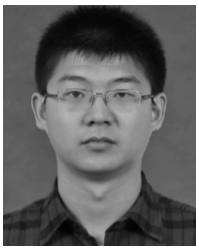

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