A Digital Signal Recovery Technique Using DNNs for LEO Satellite Communication Systems

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Abstract—This paper proposes a new digital signal recovery (DSR) technique for next-generation power efficient low Earth orbit (LEO) satellite-to-ground communication systems, which feature additive white Gaussian noise (AWGN) channel and significant power variation. This technique utilizes the prior knowledge (i.e., nonlinearities of radio frequency power amplifiers (RF-PAs)) of space-borne transmitters to improve the quality of the signal received at ground stations by modeling and mitigating the imperfection using deep neural networks (DNNs). Benefiting from its robustness against noise and power variation, the proposed DNN based DSR technique (DNN-DSR), can correct high signal distortions caused by the nonlinearities and hence allows RF-PAs to work close to their saturation region, leading to a high power efficiency of the LEO satellites. This work has been validated by both simulations and experiments, in comparison with the power back-off technique as well as memory polynomial based DSR solutions. Experimental results show that the DNN-DSR technique can increase the drain efficiency of the space-borne RF-PA from 32.6% to 45% while maintaining the same error vector magnitude as the power back-off technique. It has also been demonstrated that the proposed DNN-DSR technique can handle a signal power variation of 12 dB, which is challenging for conventional solutions.

Index Terms—deep learning, deep neural network, digital signal recovery, linearization, power amplifier, radio frequency, low Earth orbit, satellite-to-ground communication.

I. INTRODUCTION

NOWADAYS, satellite communication has drawn great attention in the space industry due to the rapid technological advancement of low Earth orbit (LEO) satellites. LEO satellites are deployed at the altitude of 500–1500 km with an orbital period of shorter than two hours [1]. The fast movement of the LEO satellites leads to a very limited transmission window with ground stations, approximately 10 minutes per pass. As the amount of data grows, transmitting as much data as possible is an increasing demand for LEO communication systems within the limited transmission window.

Orthogonal frequency division multiplexing (OFDM) techniques have been investigated for satellite communication to achieve a high transmission data rate [2]. However, the OFDM signal features a high peak-to-average power ratio (PAPR). This makes it very sensitive to system nonlinearities, which in most of the cases are mainly contributed by radio frequency power amplifiers (RF-PAs). Normally, the RF-PA works in saturated or near-saturated mode to achieve a high power efficiency, resulting in a high nonlinearity. The nonlinear distortion severely damages the signal quality (i.e., in-band distortion and out-of-band spectral regrowth), and hence degrades the transmission rate. Therefore, handling the nonlinearity of the RF-PA has been an indispensable part of LEO satellite-to-ground communication systems.

Power back-off techniques, which are illustrated in Fig. 1(a),
are commonly used in LEO satellite-to-ground communication systems. The power back-off technique reduces the input power of the RF-PA to mitigate the nonlinear distortion of transmitted signals. Without consuming extra hardware resources and performing extra signal processing, space-borne transmitters become simple, reliable, and stable. However, the main drawback of the power back-off technique is the low power efficiency of the RF-PA. To improve the power efficiency of the RF-PA, different digital pre-distortion (DPD) techniques have been reported, such as lookup tables [3] and memory polynomial (MP) [4]. Also, deep neural networks (DNNs) based DPD techniques [5], [6] have been investigated due to their great linearization performance and attractive properties (e.g., robustness to dynamic nonlinearities of RF-PAs). As illustrated in Fig. 1(b) DPD techniques pre-distort the input of RF-PAs to compensate the nonlinearity, and as a result the output of the RF-PAs appears to be linearly amplified. DPD techniques could obtain both the superior signal quality and the high power efficiency. However, applying the DPD techniques into satellite communication is a great challenge due to the stringent limitation of power and computing resources available on satellites.

In this paper, we propose a new digital signal recovery (DSR) technique based on DNNs for next-generation power efficient LEO communication systems without using space-borne computing resources. The system block diagram is shown in Fig. 1(d). The novelty of this technique is the concept of capturing the nonlinearity of the space-borne RF-PA for recovering the received signal at the ground station. Very few work focusing on the DSR technique [7] has been reported previously. It is also possible to implement the proposed concept using the MP technique, as shown in Fig. 1(c). However, since the MP technique is power dependent, it only works under ideal channel conditions with a steady signal power. As illustrated in the results in the validation section, the MP-DSR technique does not work for satellite-to-ground communications which features time-varying channel effects, especially the time-varying signal power.

Driven by the more and more powerful computing resources and available data, DNNs have shown attractive potential in many different fields [8], [9]. Recently, a few DNN based techniques for boosting the performance of communication systems, such as autoencoders [10]–[12] have been reported. The proposed DNN-DSR concept is in line with this direction of the technology development. Benefiting from the robustness to noise provided by the DNN itself [8]–[10] and the power independence contributed by batch normalization layers, the proposed concept is becoming possible. This enables the space-borne RF-PA to work close to its saturation region, and hence achieves higher power efficiency.

The experimental validation compares the DNN-DSR technique with the power back off technique (Fig.1(a)) and the MP-DSR technique(Fig.1(c)). The comparison with the power back-off technique is with the focus on the drain efficiency of the space-borne RF-PA. And the comparison with the MP-DSR technique is focusing on the adjacent channel power rate (ACPR), AM-AM distortion, and error vector magnitude (EVM). The rest of this paper is organized as follows. Section II investigates the dynamic transmission condition. Section III shows the DNN theory, and section IV introduces the DNN-DSR technique. Validation of the proposed DNN-DSR technique is given in section V. Section VI presents the conclusion of this paper.

II. DYNAMIC TRANSMISSION CONDITION

A. Time-varying signal power

Generally, when the elevation angle of a LEO satellite is greater than $5^\circ$, the transmission link is established [13], as shown in Fig. 2. At time $t_1$, the transmission link is set up with the longest transmission distance denoted as $d_1$. Meanwhile, the satellite is moving towards the ground station with a velocity of $v_1'$. At time $t_2$, the transmission distance is the shortest, and the relative velocity $v_2'$ is equal to zero. Finally, the satellite departs from the ground station with a relative velocity of $v_3'$. The geometry relation between the elevation angle and the transmission distance can be built up in Fig. 3, where $R_e$ represents the radius of Earth which is 6371 km, $h_0$ denotes the orbital altitude of the satellite, the elevation angle is represented as $\varepsilon$, and the transmission distance is denoted as $d$. Hence, the geometry relation between the elevation angle and the transmission distance is written as

$$
\frac{R_e + h_0}{\sin \left( \frac{\pi}{2} + \varepsilon \right)} = \frac{R_e}{\sin \sigma} = \frac{d}{\sin \left( \frac{\pi}{2} - \varepsilon - \sigma \right)}.
$$

(1)
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III. THE DNN THEORY

DNNs are composed of fully connected (FC) layers, batch normalization (BN) layers, and active function layers. Also, each hidden layer consists of one FC layer, one BN layer, and one active function layer.

In the FC layer, weights and biases are expressed by $W_i$ and $B_i$, respectively, where $i$ denotes the $i$-th FC layer. Then, the output of the $i$-th FC layer $y_i$ is defined as

$$y_i = W_i x_i + B_i,$$

where $x_i$ is the input of the $i$-th FC layer. The number of neurons in each FC layer is determined by iterative tests to achieve the best performance.

Then, the output of the FC layer is sent into the BN layer. The BN layer normalizes the mean and variance of the input data to 0 and 1 respectively, and then gives the input data a new mean and variance. In this way, the time cost of the training step can be significantly reduced [18]. The output of the BN layer can be written as

$$\hat{y}_i = \gamma \frac{y_i - E[y_i]}{\sqrt{\text{Var}[y_i] + \epsilon}} + \beta,$$

where $\hat{y}_i$ is the output of the BN layer. Also, $\gamma$ and $\beta$, which represent the new mean and variance of the input data, are the scaling and shifting parameters respectively. Note that, $\gamma$ and $\beta$ are learnable parameters. Besides, $\epsilon$ is a constant parameter that prevents the denominator from being zero. Generally, $\epsilon$ is set to 0.001.

Finally, the output of the BN layer is sent into the active function layer, which is expressed by $F(\cdot)$. $F(\cdot)$ is a nonlinear function such that the DNN becomes nonlinear. Owing to the nonlinearity, the DNN can fit arbitrary curves. The rectified linear units (ReLU) active function is used in the DNN-DSR technique for accelerating convergence [19]. The ReLU function is defined as

$$F_{\text{ReLU}}(u) = \max(u, 0),$$

where $u$ denotes the input of the ReLU function. Then, the output of one hidden layer can be expressed by

$$x_{i+1} = \max(\hat{y}_i, 0),$$

where $x_{i+1}$ is the input of the next FC layer. This procedure that transfers the raw data from the first layer to the last layer is called the forward propagation. Useful features are extracted from the raw data layer by layer.
In this paper, the Smooth L1 loss function is utilized for regression due to its robustness to outliers [20]. Outliers represent the abnormal I/Q values that are extremely far from the true values in this work. The Smooth L1 loss function is represented by

$$\text{Loss}(O, T) = \frac{1}{N} \sum_{i=1}^{N} E_i,$$  \hspace{1cm} (8)

where $O$ and $T$ are the predicted values and true values respectively, and

$$E_i = \begin{cases} 0.5 (O_i - T_i)^2, & \text{if } |O_i - T_i| < 1 \\ |O_i - T_i| - 0.5, & \text{otherwise} \end{cases}.$$  \hspace{1cm} (9)

Besides, the adaptive moment estimation (Adam) algorithm is used for updating the weights of the DNN due to its computational efficiency [21]. The procedure that transfers the loss from the last layer to the first layer for updating the weights of the DNN is called backward propagation.

IV. PROPOSED DNN-DSR TECHNIQUE

A. Procedure of the DNN-DSR technique

The procedure of the DNN-DSR technique includes two steps (i.e., offline training and online applying), as shown in Fig. 5. In the offline training step, the DNN is trained to capture the nonlinearity of the RF-PA. The output and input of the RF-PA are set to the training data and true values, respectively, as shown in Fig. 5(a). Then, the DNN gradually learns the nonlinearity of the RF-PA during the training procedure. When the loss is under the preset threshold or no longer converged, the training step is finished. After training, the functionality of the DNN, denoted as $u(t)$, is an optimal estimation of $G_t \cdot h^{-1}(t)$, where $G_t \cdot G_r \approx 1$, and $G_t$ is the gain of the RF-PA. In the online applying step, the trained DNN is placed at the ground station operating in the digital baseband. Meanwhile, the RF-PA that is learned by the DNN is assembled on the LEO satellite, as shown in Fig. 5(b).

Furthermore, considering extending the lifetime of satellites, the DNN-DSR technique needs to work with different or aging RF-PAs. In the first case, several backup RF-PAs will be assembled on the space-borne transmitter before the satellite is launched. Therefore, it provides enough time for the DNN-DSR technique to learn the nonlinearity of each RF-PA. In the second case, the nonlinearity of the space-borne RF-PA varies with the temperature, voltage supply, and time. The DNN-DSR technique has the potential to update the DNN model online via transmitting training sequences from the satellite to the ground station without a feedback loop. However, online
updating of the DNN model is not the main focus of this paper, and it will be included in future work.

B. Principle analysis

The DSR technique typically encounters two critical challenges, which are the time-varying signal power and the AWGN. The DNN-DSR technique has two important features which well copes with these two challenges.

Firstly, the DNN-DSR technique is inherently robust to noise. In [8]–[10], DNNs appear robustness to noise if the training data are intentionally and randomly corrupted by noise. In other words, DNNs can learn the characteristics of the noise from the corrupted training data, and use the knowledge for improving the extraction of the data features. In this work, the captured output and input signals of RF-PAs are polluted by the thermal noise, which is a kind of AWGN. On the other hand, the principle of the MP-DSR technique is that different amplitudes of the output signal of the RF-PA are multiplied by different gains. Then, the output of the MP-DSR model appears to be linearly amplified. Therefore, the DNN-DSR technique appears more robust to the AWGN than the MP-DSR technique.

Another important feature of DNN-DSR is the power independence, which is achieved by including BN layers. The structure of the exploited DNN is shown in Fig. 6, where \( r_I[n] \) and \( r_Q[n] \) are Cartesian I/Q components of received signals. \( \hat{r}_I[n] \) and \( \hat{r}_Q[n] \) are the I/Q components of recovered signals. \( N_{MD} \) is the number of past samples that corresponds to the memory depth of MP techniques. \( (a) \), \( (b) \), \( (c) \), and \( (d) \) are the input of the DNN, the input of the first BN layer, the output of the first BN layer, and the output of DNN, respectively. The time-domain signals of \( (a) \), \( (b) \), \( (c) \), and \( (d) \) are shown in Fig. 7. It can be observed that the input power variation of the DNN has insignificant effect on the output of the DNN, and the first BN layer can keep the output power at a constant level. However, the MP-DSR model severely suffers from the time-varying signal power (Fig. 7(e)).

The mathematical model of the BN layer is shown in Fig. 6, corresponding to Eq. (5). The mean and the variance of the training data are both normalized by BN layers. In this paper, the mean and variance of the training data indicate the mean power and power variation of the input signal, respectively. Therefore, the BN layers can remove the characteristic of the time-varying signal power from the signal received at ground stations. Because of this advantage, the BN layer is inserted in every hidden layer, such that the time-varying signal power no longer affects the output of the DNN-DSR model. Therefore, the DNN-DSR technique is power independent by using the DNN with BN layers. However, referring to the principle of the MP-DSR technique, if the entire power level of the received signal changed, the MP coefficients would become completely incorrect. Therefore, the MP-DSR technique is a power dependent model and unsuited for the target application.

V. Validation

A. Experimental setups

The radio frequency signal is generated by the signal generator with MATLAB, as shown in Fig. 8. The signal generator and the signal analyzer are R&S SMBV100A [22] and R&S FSQ26 [23] respectively. A CGH40006P RF-PA [24], which is a gallium nitride high electron mobility transistor, is used for testing the recovery performance. Furthermore, to have enough power to drive the RF-PA, the output of the signal generator is pre-amplified by a linear power RF amplifier [25]. The gain of the linear power RF amplifier can be approximately regarded as a constant number as the output power of the signal generator varies. The experimental environment is shown in Fig. 9.

In order to completely learn the nonlinearity of the RF-PA, the signal that is sensitive to the nonlinear distortion should be chosen in the experiments. In other words, it is necessary to find a signal with a high PAPR. In this experiment, we generate an OFDM signal with a PAPR of 10.06 dB directly from the signal generator. On the other hand, the frequency band and the carrier frequency of the signal are not the major concerns in this work. As C-band communication systems have already been deployed in satellites [26], the frequency band and the frequency point are set to 10 MHz and 3.5 GHz, respectively. Moreover, different input power levels of the RF-PA are taken into account for deriving the relation between the power efficiency of the RF-PA and the recovery performance, and different attenuators are inserted between the RF-PA and

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**Fig. 8. Schematic diagram of the data collection system.**

**Fig. 9. Entire experimental environment.**
the signal analyzer to simulate the varying signal power.

On the other hand, the number of neurons and layers should be set appropriately. If the number of hidden layers and neurons is too small, the DNN cannot extract sufficient features from training data for linearizing the RF-PA (i.e., underfitting). In contrast, if the number of hidden layers and neurons is too large, the DNN will fit training data too closely (i.e., overfitting) and time will be wasted on training without any performance improvement or even have the risk of poor application performance. After testing the recovery performance versus different numbers of the neurons and layers, two hidden layers employed with 300 and 150 neurons respectively, are shown in Table I. It can be clearly seen that if the size of the DNN is large enough (i.e., two hidden layers with 300 and 150 neurons respectively in this work), the recovery performance will not increase as the size of the DNN increases. Considering the memory effect of the RF-PA, the memory depth is set to 7. Since the training data and the true values are two complex-valued sets (I and Q), the number of neurons of the input layer and output layer is set to 14 and 2 respectively. In order to make the comparison fair, the memory depth is set to 7. Since the DSR technique is operated at the receiver side, we should pay more attention on the EVM rather than the ACPR to verify the DSR technique. The EVM is used to evaluate the performance of transmitters and receivers. In [27] and [28], the EVM-BER relation with different digital modulations is written as

$$\text{EVM} = \frac{1}{M} \left( \frac{1}{2} \sqrt{\frac{1}{M-1} k^2 \text{EVM}_{\max}^2} \right).$$

where EVM_{\max} is measured when the maximum power of the ideal constellation vector is normalized to 1. The values of k^2 with different digital modulations are shown in Table II. Referring to (11), the EVM-BER relation is described in Fig. 10(a). As shown in the figure, when the EVM is lower than 10%, decreasing the EVM can dramatically improve the BER performance by several orders of magnitude. Then, from Fig. 10(b) that depicts different digital modulations with their theoretical BER curves, the EVM performance has a close connection with the output power of the transmitter.

D. Efficiency analysis

As mentioned in section I, there is a trade-off between the nonlinearity and power efficiency of the RF-PA. That trade-off can be clearly observed in Table III, where the output of the RF-PA is analyzed in terms of the ACPR and EVM with different input powers of the RF-PA.

DNN-DSR technique needs more computing resources than the MP-DSR technique, it would not limit the development of the deep learning technology in the space industry.

TABLE I

<table>
<thead>
<tr>
<th>Number of hidden layers and neurons</th>
<th>EVM</th>
<th>ACPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-10</td>
<td>2.55%</td>
<td>-40.19 dBc</td>
</tr>
<tr>
<td>1-100</td>
<td>2.38%</td>
<td>-40.65 dBc</td>
</tr>
<tr>
<td>1-300</td>
<td>1.83%</td>
<td>-43.01 dBc</td>
</tr>
<tr>
<td>1-500</td>
<td>1.59%</td>
<td>-43.91 dBc</td>
</tr>
<tr>
<td>1-10, 2-10</td>
<td>2.16%</td>
<td>-41.82 dBc</td>
</tr>
<tr>
<td>1-100, 2-100</td>
<td>1.51%</td>
<td>-44.63 dBc</td>
</tr>
<tr>
<td>1-100, 2-100</td>
<td>1.37%</td>
<td>-45.95 dBc</td>
</tr>
<tr>
<td>1-300, 2-150</td>
<td>1.33%</td>
<td>-46.74 dBc</td>
</tr>
<tr>
<td>1-500, 2-500</td>
<td>1.27%</td>
<td>-46.73 dBc</td>
</tr>
</tbody>
</table>

1 The EVM and ACPR of the output signal of the RF-PA without DSR techniques are 8.06% and -32.06 dBc respectively.

2 The ACPR of the input signal of the RF-PA is -50.03 dBc.

TABLE II

<table>
<thead>
<tr>
<th>Modulation</th>
<th>PSK</th>
<th>16QAM</th>
<th>32QAM</th>
<th>64QAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>k^2</td>
<td>1/5</td>
<td>9/5</td>
<td>17/10</td>
<td>7/3</td>
</tr>
</tbody>
</table>

C. Relation between EVM, BER and SNR

The BER = 1 - M^{-1/2} \frac{\text{EVM}}{0.5 \log_2 M} \text{erfc} \left[ \sqrt{\frac{1}{5 (M-1) k^2 \text{EVM}^2_{\max}}} \right].
Fig. 10. Inter-dependencies between (a) BER and EVM, and (b) the theoretical BER curves for different digital modulations.

**TABLE III**

<table>
<thead>
<tr>
<th>Input power (dBm)</th>
<th>33.85</th>
<th>33.35</th>
<th>32.85</th>
<th>32.5</th>
<th>32</th>
<th>30.95</th>
<th>30.5</th>
<th>29.5</th>
<th>28.5</th>
<th>27.5</th>
<th>26.5</th>
<th>26</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output power (dBm)</td>
<td>38.6</td>
<td>38.4</td>
<td>38.15</td>
<td>37.9</td>
<td>37.7</td>
<td>37.5</td>
<td>36.7</td>
<td>36.45</td>
<td>36.1</td>
<td>35.71</td>
<td>35.1</td>
<td>34.3</td>
</tr>
<tr>
<td>Drain efficiency</td>
<td>46.2%</td>
<td>45.0%</td>
<td>43.6%</td>
<td>42.3%</td>
<td>41.7%</td>
<td>40.9%</td>
<td>38.3%</td>
<td>37.7%</td>
<td>36.6%</td>
<td>34.8%</td>
<td>32.6%</td>
<td>29.8%</td>
</tr>
<tr>
<td>EVM</td>
<td>24.6%</td>
<td>23.0%</td>
<td>21.2%</td>
<td>19.5%</td>
<td>18.0%</td>
<td>14.8%</td>
<td>12.2%</td>
<td>11.1%</td>
<td>10.1%</td>
<td>9.4%</td>
<td>8.1%</td>
<td>7.4%</td>
</tr>
<tr>
<td>ACPR</td>
<td>-20.9 dBc</td>
<td>-21.6 dBc</td>
<td>-22.4 dBc</td>
<td>-23.2 dBc</td>
<td>-24.0 dBc</td>
<td>-25.9 dBc</td>
<td>-27.8 dBc</td>
<td>-28.8 dBc</td>
<td>-29.8 dBc</td>
<td>-30.6 dBc</td>
<td>-32.1 dBc</td>
<td>-33.0 dBc</td>
</tr>
</tbody>
</table>

Fig. 11. Measured recovery performance comparison of the DNN-DSR technique and the MP-DSR technique in terms of the ACPR and the EVM alone with the drain efficiency of the RF-PA. (a) Measured relation between the drain efficiency and the EVM, (b) Measured relation between the drain efficiency and the ACPR.

modulation. Fig. 11(a) specifies that the DNN-DSR technique can achieve almost 45% of the drain efficiency when an EVM of 8% is achieved, while the drain efficiency is only 32.6% by using power back off to obtain the same EVM level. In other words, the drain efficiency of the RF-PA can be increased from 32.6% to 45% using the DNN-DSR technique.

**E. Noise robustness analysis**

With a small input power of the RF-PA, it appears a slight nonlinearity, resulting in a low EVM level. It is clear to see
how the EVM changes under the AWGN channel. In this work, we utilize a small input power to analyze the recovery performance, which corresponds to the input power of 26 dBm in Table. III.

Fig. 12 describes the recovery performance of the two DSR techniques under the AWGN channel, in terms of the EVM and the ACPR. As can be seen, the recovery performance of the DNN-DSR technique is always better than that of the MP-DSR technique. Similarly, the ACPR is not important to qualify the performance of the DSR technique.

When the SNR is higher than 24 dB, the DNN-DSR technique outperforms the MP-DSR technique in SNR with 3 dB improvement under the same level of the EVM. In other words, the transmitted power can be reduced by up to 3 dB while maintaining the same EVM (i.e., the BER) by using the DNN-DSR technique instead of the MP-DSR technique. Particularly, when the SNR is 27 dB, the DNN-DSR technique can obtain approximately 2% improvement of the EVM, compared with the MP-DSR technique. Then, as shown in Fig. 10(a), above three orders of magnitude improvement of the BER can be achieved for the OFDM-32QAM modulation.

When the SNR is lower than 24 dB, the MP-DSR technique is not working at all. Compared with the communication system without using any linearization techniques (i.e., the gray line), if the EVM is required to be 9%, the DNN-DSR technique can achieve approximately 4 dB improvement of the SNR. Equivalently, the transmitted power can be reduced by 4 dB exploiting the DNN-DSR technique while maintaining the same BER. Furthermore, when the SNR is around 23 dB, above 2.5% improvement of the EVM can be obtained by using the DNN-DSR technique, compared with the communication system without linearization techniques. Then, for the OFDM signal with 16QAM modulation, from Fig. 10(a), about two orders of magnitude improvement of the BER can be obtained.

F. Power independence analysis

Since the input power of the RF-PA can affect the nonlinearity of the RF-PA, the input power should be kept constant in the power independence experiment. As an experiment, we also select a signal with a small input power but still contains sufficient nonlinear distortion, corresponding to the input power of 27.6 dBm in Table. III. Then, three groups of the output signals of the RF-PA, denoted as $S_1$, $S_2$, and $S_3$ respectively, are captured using different attenuators. The only difference between them is the power level, where the attenuation of the signal $S_2$ is regarded as 0 dB. Then, the attenuation coefficients of the signal $S_1$ and $S_3$ are relatively 6 dB and -6 dB, respectively, such that the signal power variation of the whole satellite communication window can be completely covered. To validate the power independence, signal $S_2$ is chosen to train the DNN and the MP model. The trained DNN and MP are both called $M_2$. Then, the signals $S_1$ and $S_3$ are used to finish the recovery.

Fig. 13 specifies the recovery performance comparison between the DNN-DSR technique and the MP-DSR technique with different signal powers, in terms of the power density spectrum (PSD) and AM-AM curve. The gains, shown in Fig. 13(b) and Fig. 13(d), are measured with the effect of attenuators.

In contrast to the DNN-DSR technique, the MP-DSR technique is not working at all when the received signal power changes. Besides, it can be clearly observed in Fig. 13(b) and Fig. 13(d) that the output power of the DNN always remains constant regardless of the change in the input power of the DNN. However, the output power of the MP-DSR technique varies with the input power.

The measured EVM and ACPR are given in Table. IV, where superior recovery performance of the DNN-DSR technique can be seen over the MP-DSR technique (Fig. 13(a)). The benefits of the DNN-DSR technique are further concluded as follows:

1) The DNN-DSR technique corrects the signal distortion caused by space-borne RF-PAs at the ground station, eliminating the need of DPD at the satellite, and hence saves space-borne computing resources.

2) The drain efficiency of the RF-PA can be increased to above 45% by using the DNN-DSR technique. Compared with the power back-off technique, the DNN-DSR technique can obtain up to 13% increase of the drain efficiency while maintaining the same EVM performance.

3) The MP-DSR technique cannot tolerate time-varying received signal power caused by time varying communication distances. However, this is not an issue for the DNN-DSR technique due to the BN layer.

4) The DNN-DSR technique is more robust to the AWGN than the MP-DSR technique.

VI. CONCLUSION

In this paper, we introduced a new DSR technique based on DNNs (DNN-DSR) for LEO satellite-to-ground communications. The DNN-DSR technique allows the space-borne RF-PA to work close to its saturation region, and hence has the ability to significantly increase the power efficiency of the satellites. The DNN-DSR technique features robustness against the noise and power variation, which makes it suitable to handle the additive white Gaussian noise (AWGN) channel and drastic power variation featured in LEO satellite-to-ground communications, while it is very challenging for conventional approaches. Seen from the experiment validation results, the DNN-DSR approach can increase the drain efficiency of a GaN RF-PA from 32.6% to 45% compared with the power back-off linearization technique. The results also show that the DNN-DSR approach relaxes the required transmitted power from the
satellite by up to 3 dB compared with the memory polynomial based digital signal recovery (MP-DSR). With such advantages and satisfactory performance, the DNN-DSR technique provides a promising solution to improve the transmission quality for LEO satellite-to-ground communication systems.

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He has worked most of the time with joint university and industry projects and have received more than 21 M$ in direct research funding. He is currently the Project Leader of the RANGE project with a total budget of over 8 M$ investigating high performance centimetre/millimeter-wave antennas for 5G mobile phones. He has been one of the pioneers in establishing over-the-air measurement systems. The measurement technique is now well established for mobile terminals with single antennas and he was chairing the various COST groups with liaison to 3GPP and CTIA for over-the-air test of MIMO terminals. He is currently involved in MIMO OTA measurement.

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