NEURAL NETWORK-BASED NONLINEAR DISTORTION CORRECTION OF POWER AMPLIFIERS FOR UAV/DRONE VIDEO TRANSMITTION CHANNEL

Tran Van Nghia*, Bui Xuan Khoa

Abstract: *Correcting for nonlinearities of radio frequency (RF) power amplifiers (PAs) is one of the most important issues of autonomic wireless communication systems, such as portable systems, wireless video link transmitter in unmanned aerial vehicles (UAVs), OcuSync transmission system utilised on drones Mavic Pro, and etc., because system performance is largely dependent on PAs. Recently, neural networks (NNs) have achieved great success in PAs behavioral modeling and linearization due to their excellent approximation capability. This paper presents a NN based digital predistortion (DPD) using the realistic video link transmit signals captured from a Doherty PA. Its effectiveness has been validated through extensive simulations and experiments for linearizing a nonlinear Doherty PA with strong memory effect. The results show that an adjacent channel leakage ratio (adjacent channel leakage ratio) correction in excess of 20 dB is observed for the video link transmit signals and the proposed NN-based DPD can extend the linear range of the tested PA up to 4.2 dB when controlling the signals to go into deep compression region close to saturation.*

Keywords: Digital predistortion; Neural networks; Power amplifier (PA); Orthogonal frequency division multiplexing (OFDM); UAV/Drone video link.

1. INTRODUCTION

Unmanned aerial vehicles (UAV) and Drone, FlyCam are used across the world for civilian, commercial, as well as military applications [1-5]. The majority of applications require UAVs operated over distances of several ten, hundred, or even thousand kilometers under conditions of NLOS (non line of sight) and fast moving environments. These UAV/drones need significant video processing capabilities. Nowadays, airborne video link transmitter is deployed in a variety of UAVs and has become a very important device in their guidance and control system.

It is well-known that video transmitters and receivers are based on the orthogonal frequency division multiplexing (OFDM) technique [6-8] due to achievements of high spectrum efficiency, robust against intersymbol interference and frequency-selective fading channels. The Kimpok company's field-proven products are developed for UAV/Drones, which can transmit to fixed stations up to several hundred kilometers LOS and several ten kilometers NLOS distance [6]. However, one of the major problems of OFDM technology is that OFDM signal has a high peak-to-average-power ratio (PAPR). It requires a large dynamic range of power amplifiers (PA), thereby significantly increasing the cost and the power consumption. This problem is more important for UAV/drones since the efficiency of PA is critical due to the limited battery power. In general, even linear PAs contain non-idealities that can cause performance degradation of the systems. When input power increases beyond a certain point, output power begins to increase in a nonlinear fashion. This causes out-of-band (OOB) radiation that affects signals in adjacent bands (the transmitter will draw more power), and in-band (IB) distortions that result in bit error rate (BER) increase. To mitigate this performance degradation of nonlinear PAs, there are several approaches such as: PAPR reduction [9,

10] and PA linearization [11, 12]. Digital pre-distortion (DPD) is one of the most cost-effective linearization techniques. It takes full advantage of advances in digital signal processors of FPGA chip (ARM, MicroBlaze).

Inspired by the augmented real-valued time-delay neural networks (ARVTDNN) [11] and DPD based on memory polynomial and indirect learning architecture (ILA) [12], this paper proposes a two-hidden layer NN for the DPD using the ILA algorithm. Another NN is used to model the PA for the purpose of evaluating the NN-based DPD. The proposed NN-based DPD avoids problems seen with standard ILAs (the measurement of PA's output could be noisy, thus, the adaptive algorithm converges to biased values) and improves the overall performance. The simulations and experiments demonstrate the effectiveness of the proposed scheme using Doherty PA [13] at 2.4 GHz. The experimental results show promising linearization capability.

2. NEURAL NETWORKS FOR BEHAVIORAL MODELING OF PA AND DPD

The radio frequency (RF) front end of most systems consists of a ADC (analog-to-digital converter), DAC (digital-to-analog converter), up/down-converters and PA. The PA is one of the most power-hungry devices, but is also the main source of nonlinear distortion in the system. DPD allows PAs to be driven harder into compression while meeting linearity requirements, as shown in figure 1.

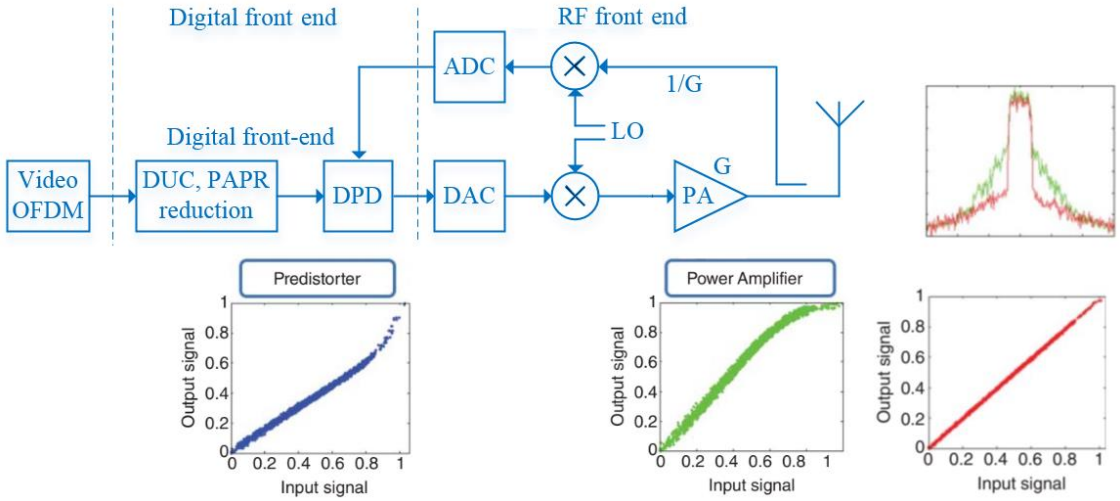


Figure 1. *Block diagram of PA linearization.*

Nowadays, ADCs, DACs and up/down-converters can be manufactured in an integrated circuit (IC), such as RF transceivers ad9361 [14], ad9371, etc. These transceivers use a direct conversion architecture that achieves high modulation accuracy with ultralow noise (≤ -157 dBm/Hz noise floor). Therefore, RF front end imperfections are determined by PA, thus, RF front end nonlinearity models can be reduced to PA nonlinearity models.

The input of the RF front end is applied to DAC, while the ADC output is also the RF front end output that is sent to the DPD. These signals are baseband complex ones. Accordingly, we can model the PA as a discrete time system.

As widely presented in the literature, NNs are able to approximate any nonlinear

function, making them become an increasingly attractive solution for the PA and DPD behavioral modeling (see figure 2, on the left-hand side). The PA NN is used to provide a model that represents the best fit to PA nonlinearity. The RF front end and the PA NN are driven by the same input while its output supplies the desired response for the PA NN. The function of the DPD NN is to provide an inverse model that represents the best fit to an inverse nonlinearity of the PA.

Basically, NN structures are multiple-input multiple-output, which takes the in-phase (I) component and quadrature (Q) phase component of the baseband OFDM signal in processing activities. For multicarrier modulation signals, the memory effects of PAs cannot be neglected. Memory effects are more evident when PA is excited by higher bandwidth signals. To consider memory effects, tapped delay lines are added to the NN topology, which takes current and past signal samples applied to its inputs (see figure 2, on the right-hand side). The NN input signal vector of the order 2(m-1)-by-1, including real values of current and past samples can be represented as

$$u_{\text{in}}(n) = \left[I_{\text{in}}(n), I_{\text{in}}(n-1), \ldots, I_{\text{in}}(n-M), Q_{\text{in}}(n), Q_{\text{in}}(n-1), \ldots, Q_{\text{in}}(n-M)\right] \quad (1)$$

where M is the memory depth of the investigated PA; $I_{\text{in}}(n)$ and $Q_{\text{in}}(n)$ represent the I and Q components of the current samples; $I_{\text{in}}(n\text{-}k)$ and $Q_{\text{in}}(n\text{-}k)$, k = 1, 2, ⋯, M, denote the I and Q components of the past (delayed) samples.

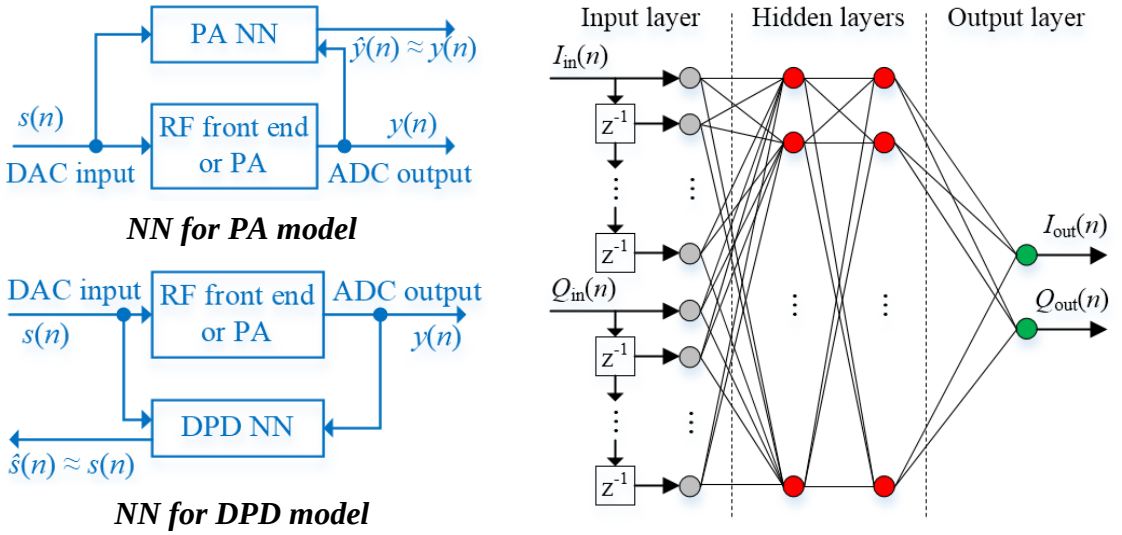


Figure 2. *The NN for PA and DPD models, and their topology.*

The double-output of the NN is expressed as

$$I_{\text{out}}(n) = f_1\left(u_{\text{in}}(n)\right) \quad (2)$$

$$Q_{\text{out}}(n) = f_2\left(u_{\text{in}}(n)\right) \quad (3)$$

where f_1 and f_2 are functions modeled by the NN at any instant (n).

We use a feed-forward NN that is fully connected. The net at any layer is equal to the bias plus the sum of the products of the input signals and corresponding weights, which is given by

$$v_i^l(n) = \sum_{j=1}^{K} w_{ij}^l u_j^{l-1}(n) + b_i^l \tag{4}$$

where i denotes the i-th neuron of the current layer, j represents the j-th neuron of the previous layer, l denotes the l-th layer, w_{ij}^l is the weight that connects the j-th neuron of the (l-1)-th layer to the i-th neuron at the l-th layer, u_j^{l-1} is the input signal to the j-th neuron from the previous (l-1)-th layer, and b_i^l is the bias of the i-th neuron at the l-th layer.

The output of any layer is given as

$$o_i^l = f\left(v_i^l(n)\right) \tag{5}$$

where $f(\cdot)$ is the activation function.

The output layer has a purelin activation function, which sums up the outputs of hidden neurons and linearly maps them at the output. The nonlinear activation applied in hidden layers is chosen to be the hyperbolic tangent sigmoid (tansig) due to excellently approximating any nonlinear function such as PA. Moreover, the baseband OFDM signal samples are signed numbers while the tansig maps nonlinearity between -1 and 1; thus, using activation function is reasonable selection for PA and DPD NN. Mathematically, this function is defined as

$$\tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \tag{6}$$

Training is carried out in batch mode, supervised with a back- propagation algorithm. During the forward pass, the cost function is represented by

$$E = \frac{1}{2N} \sum_{n=1}^{N} \left[\left(I_o^d(n) - I_{\text{out}}(n) \right)^2 + \left(Q_o^d(n) - Q_{\text{out}}(n) \right)^2 \right] \tag{7}$$

where $I_o^d(n)$ and $Q_o^d(n)$ are the desired/target outputs, while $I_{\text{out}}(n)$ and $Q_{\text{out}}(n)$ are the outputs from the NN.

After that, the values of the weights and biases of the network are adjusted in backward computations using the well-known Levenberg–Marquardt algorithm that has been shown to perform exceptionally well [15]. This algorithm was selected in the training procedures for the PA model and DPD networks.

3. PROPOSED ARCHITECTURE AND SIMULATION RESULTS

DPD algorithm should be designed with the aim of preemptively distorting the waveform transmitted to counter the nonlinear effects of the PA. In essence, DPD models the transmitter's inverse characteristics. Therefore, DPD needs to be placed inline with the PA so that the cascade of the two is a linear system, as shown in figure 3. DPD should be designed in the context of the full system (realistic PA) because performance is largely dependent on the system in which it is placed. However, a realistic PA contains a number of non-idealities including nonlinearity and noise, which must also be assessed, while it cannot be used in simulations. Thus, in addition to using

DPD NN, an other NN is used to model the PA in simulations. The tapped delay lines lie at the inputs of the networks to adapt to memory effects.

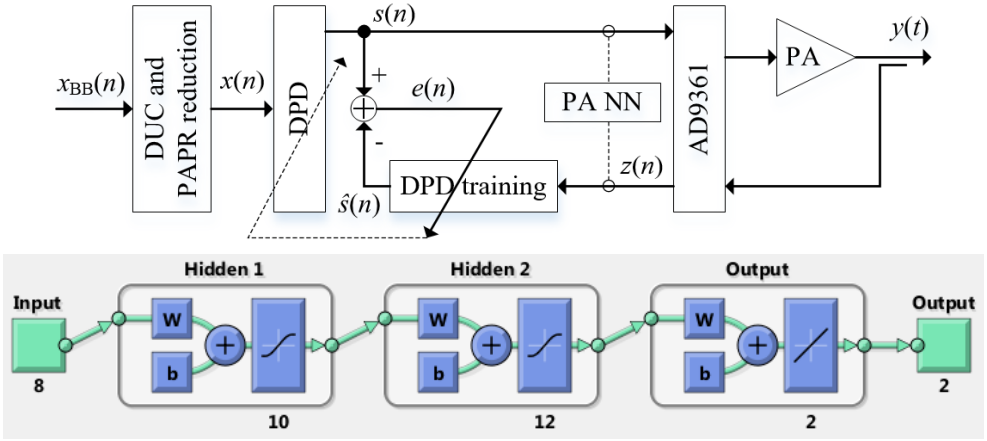


Figure 3. *Block diagram of the experimental setup and used NN structure.*

The training procedure for the aforementioned networks is based on the realistic dynamic characterization of the Doherty PA (2.400 – 2.408 GHz band is used in this paper). The baseband OFDM signal, $x_{BB}(n)$, feeds to the DUC (digital up converter) and PAPR reduction modules that interpolate the input signal by a oversampling factor of 4 and decrease its PAPR [10] to produce a signal $x(n)$. The modified tone reservation method [10] is applied to reduce PAPR of OFDM signal to 9 dB. In the data collection phase for the PA and DPD modeling, the signal $x(n)$ is sent to the ad9361, i.e. the DPD is absent and $x(n) \equiv s(n)$. About 200,000 samples of the ad9361 input, $x(n)$, and output, $z(n)$, are captured. 40,000 samples of $x(n)$ and $z(n)$ was used for training. For validation, 60,000 samples, which were selected from different segments of the overall collected data, were used.

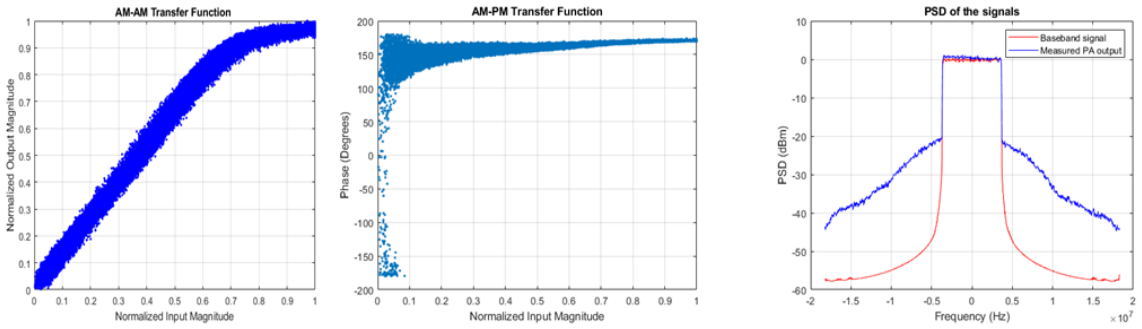


Figure 4. *The proposed modeling diagram and realistic PA characterization.*

Figure 4 shows the amplitude modulation (AM/AM) and phase modulation (AM/PM) characteristics of the actual Doherty amplifier. When adjusting PA operation point to increase beyond a 38 dBm, its output begins to increase in a nonlinear fashion from 47 dBm (= 38 dB + 9 dB of PAPR), and reaches saturation at 51.2 dBm [13]. Scattering in the gain and phase characteristics due to multiple values of gain and phase for a single value of input power indicate the presence of memory effects in the PA. The power spectral density (PSD) of the transmitter from figure 4 shows very high OOB radiation

up to -20 dB and -25 dB at the transition band and neighbor channel leakage, respectively, in comparison with the required transmit power level. It is clear that the imperfect PA not only generated very high OOB radiation, but also engendered the I/Q imbalance.

Let a PA has discrete time-domain transfer function $H_{PA}(n)$. It is the goal of PA and DPD NN to find an approximate transfer function of the PA, $H_{PA}(n)$, and its approximate inverse transfer function, $H_{PA}^{-1}(n)$. Hence, for the PA NN model, the signal $x(n)$ is applied to the input of the network as the input training data set. The captured signal $z(n)$ is used as the target training data set. To train the DPD NN, the data $x(n)$ and $z(n)$ can be used as the output and input training data. NNs consist of an input layer, hidden layers, and an output layer. The number of hidden layers and their neurons are determined during the training period of the network and by using empirical methods. In this paper, one or two hidden layers were selected. The number of neurons in the hidden layers was set to be in the range of 8-30. The number of neurons in the input layer was determined by the memory depth. The output layer contains two linear neurons. The training is carried out in MATLAB environment, and validates that the number of hidden layers was one, and the number of neurons in the hidden layers were ten and 12 for both PA and DPD NNs (see figure 3).

From figure 5, it can be seen that the proposed PA NN provides good accuracy in terms of power spectrum density for the full frequency range (-50 dB) compared to the ARVTDNN [11] (maximum of -37.93 dB), and better for in-band. The phase difference of the PA NN model and actual PA is mainly in the range of 2^0. Generally speaking, the proposed PA NN is close to the physical analogy of the PA.

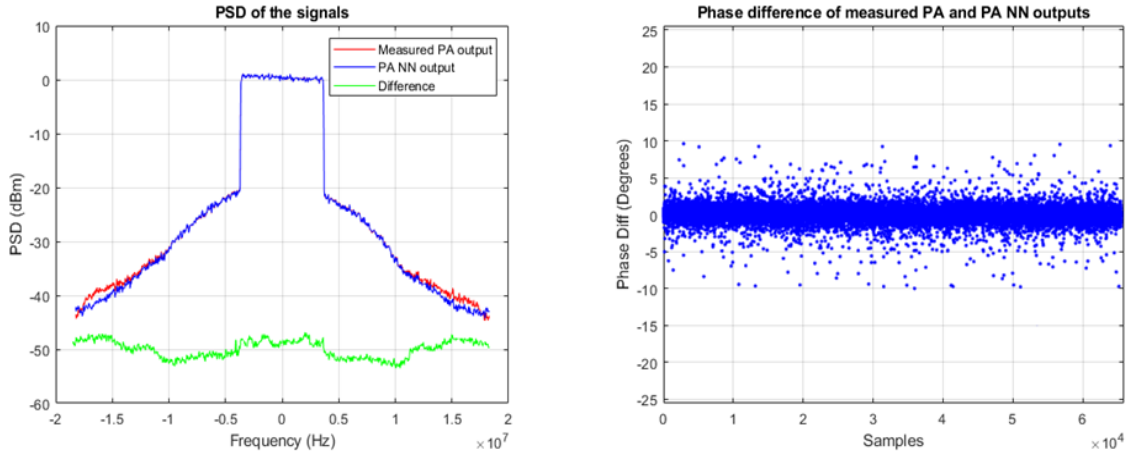


Figure 5. *Validation of the PA NN model: PSD and phase difference compared to the actual PA.*

The performance of the proposed DPD NN model is evaluated by the PA characteristic linearization (AM/AM characteristic), I/Q imbalance correction (AM/PM characteristic) and OOB radiation reduction (from the PSD curve).

Figure 6 shows the AM/AM, AM/PM characteristics and PSD curves for the delay line with memory depth 3. Each graph shows the characteristic curves of the transmitter linearized by the proposed DPD NN with and without DPD correction. It is clear from figure 6 that the proposed DPD NN has good compensation capability in the OOB radiation and I/Q imbalance. In addition, the proposed predistorter was achieved for an output power back-off (OPBO) relative to the saturation point of 51.2 dB due to its gain expansion. The linearized PA was operated at 13.2 dB OPBO, equal to 4.2 dB (= 13.2 dB – 9 dB of PAPR = 51.2 dB – 38 dB) of a gain compression. The quasi-perfect nonlinearity correction was achieved, requiring the increase of the OPBO by 4.2 dB. The PSD curves show that the OOB spectral regrowth is significantly reduced when applying DPD. About 22 dB OOB radiation reduction is observed for the neighbor channel, while the PSD curves of the linearized PA were quasi-exactly achieved with those of the actual PA for next adjacent channels.

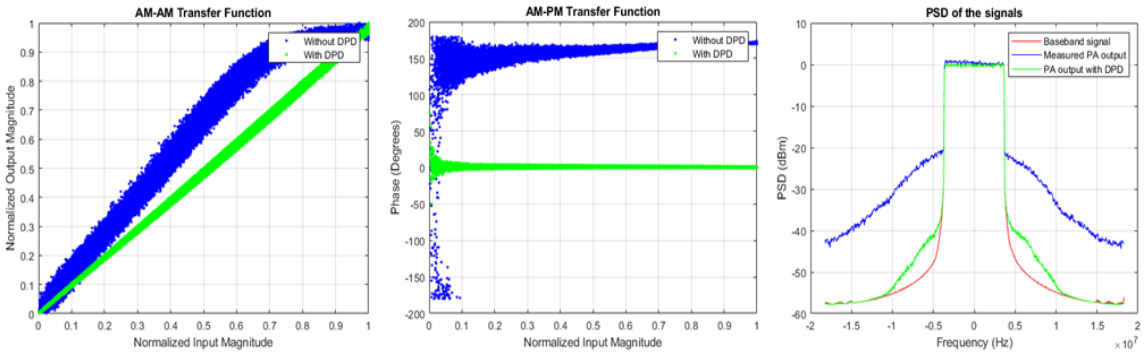


Figure 6. *Validation of the proposed DPD NN model.*

The proposed PA NN and DPD NN models provide a better performance compared to the ARVTDNN [11] for two main reasons. First, the proposed NNs employ the tansig activation function that gives the most normalized mean square error (NMSE) performance in comparison with the others [11, 15], while ARVTDNN was proposed a new activation function with a loss of NMSE performance but a marked fall in computational complexity. Second, the input signal of the ARVTDNN model contains the current and past samples and their amplitude. As widely presented in the literature, adding the amplitude of the samples is used to identify a nonlinear function as in the polynomial model [12], while NNs are able to approximate any nonlinear function. This ARVTDNN results in an improved modeling accuracy compared to the memory polynomial model using odd-order terms (see the subsection C of the section III in [11]), but its performance is equivalent to the polynomial model using both even- and odd-order terms [12]. As well known that the causes of the memory effects can be attributed to thermal constants of the active devices or components in the biasing network that have frequency dependent behaviors. As a result, the current output of the PA depends not only on the current input, but also on the past input. The tapped delay lines in the proposed NN topology take current and past samples to consider PA memory effects. Therefore, the NN with delay lines in this paper makes it achieve both nonlinearity and memory effects.

4. CONCLUSIONS

In this paper, we propose the NN topologies for modeling nonlinear PA and DPD. The NNs consist of two hidden layers with ten and 12 neurons. The linearization capability of the proposed NN predistorter was validated for a highly nonlinear Doherty PA with strongly memory effect. The measurement results confirm that the linearization performance of the predistorter is about 22 dB for the neighbor channel and quasi-perfect for next adjacent channels. The increase of the OPBO by 4.2 dB is observed when applying DPD.

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TÓM TẮT

SỬA MÉO PHI TUYẾN BỘ KHUẾCH ĐẠI CÔNG SUẤT DỰA TRÊN MẠNG NƠ-RON CHO KÊNH TRUYỀN VIDEO CỦA UAV/DRONES

Khắc phục tính phi tuyến của bộ khuếch đại công suất (PA) dải tần số vô tuyến là một trong những vấn đề quan trọng nhất của hệ thống vô tuyến hoạt động độc lập, chẳng hạn như hệ thống mang xách, bộ phát đường liên kết video vô tuyến nằm trong máy bay không người lái (UAV), hệ thống OcuSync được sử dụng trên drone Mavic Pro, v.v., vì hiệu suất hệ thống phụ thuộc phần lớn vào các PA. Gần đây, mạng nơ-ron (NN) đã đạt được thành công lớn trong việc mô hình hóa hành vi và tuyến tính hóa PA nhờ vào khả năng xấp xỉ tuyệt vời của chúng. Bài báo này trình bày bộ méo trước tín hiệu số (DPD) dựa trên NN sử dụng tín hiệu truyền của kênh video thực tế được trích xuất từ Doherty PA. Hiệu quả của DPD được minh chứng thông qua các mô phỏng và thử nghiệm đầy đủ để tuyến tính hóa một Doherty PA phi tuyến có hiệu ứng nhớ mạnh. Các kết quả cho thấy rằng, khả năng sửa mức bức xạ ra kênh lân cận đạt trên 20 dB đối với các tín hiệu kênh liên kết video và DPD dựa trên NN được đề xuất làm tăng được dải tuyến tính cho PA trong thử nghiệm lên đến 4.2 dB khi điều khiển các tín hiệu đi vào vùng nén sâu gần vùng bão hòa.

Từ khóa: Méo trước số; Mạng nơ-ron; Bộ khuếch đại công suất (PA); Phân kênh tần số trực giao (OFDM); Đường liên kết video của UAV/Drone.

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