AI-Driven Demodulators for Nonlinear Receivers in Shared Spectrum with High-Power Blockers

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***Abstract*—Research has shown that communications systems and receivers suffer from high power adjacent channel signals, called blockers, that drive the radio frequency (RF) front end into nonlinear operation. Since simple systems, such as the Internet of Things (IoT), will coexist with sophisticated communications transceivers, radars and other spectrum consumers, these need to be protected employing a simple, yet adaptive solution to RF nonlinearity. This paper therefore proposes a flexible data driven approach that uses a simple artificial neural network (ANN) to aid in the removal of the third order intermodulation distortion (IMD) as part of the demodulation process. We introduce and numerically evaluate two artificial intelligence (AI)-enhanced receivers—ANN as the IMD canceler and ANN as the demodulator. Our results show that a simple ANN structure can significantly improve the bit error rate (BER) performance of nonlinear receivers with strong blockers and that the ANN architecture and configuration depends mainly on the RF front end characteristics, such as the third order intercept point (IP3). We therefore recommend that receivers have hardware tags and ways to monitor those over time so that the AI and software radio processing stack can be effectively customized and automatically updated to deal with changing operating conditions.**

***Index Terms*—AI, ANN, IMD, IP3, spectrum sharing.**

I. Introduction

Due to proliferation of smart applications, spectrum sharing has become a key enabler in order to accommodate massive number of heterogeneous devices running those applications. Spectrum sharing greatly enhances the efficient spectral utilization, allowing transmissions in compact adjacent spectrum bands [1]. For example, the Citizens Broadband Radio Service (CBRS) band (3.55 - 3.7 GHz) in the United States has a three-tier spectrum access model where incumbent, priority access, and general authorized access users need to coexist in this new shared spectrum by following the spectrum access policy that are regulated by Federal Communications Commission [2].

In shared spectrum, the spectrum neighbors are not known a priori. Furthermore, spectrum agile devices usually have a wideband preselection filter, if any, i.e. a widely open radio frequency (RF) receiver front end. Software radios usually do no use a preselection filter and filter the received signals in the digital domain. This means that the RF front end may potentially receive many undesired signals in bands that are adjacent to the signal of interest (SOI).

In this paper we consider the case of a wideband RF filter that encompasses multiple RF channels. The SOI occupies one channel. High-power adjacent channel signals can then act as blockers and may saturate the receiver or drive the RF front end into nonlinear operation. The worst case is saturating the analog-to-digital converter (ADC), which causes clipping and severe signal distortion. In the weak nonlinearity region, on the other hand, the low-noise amplifier (LNA) is driven in its nonlinear region causing signal compression. Two adjacent channel signals entering a nonlinear device, such as an LNA, cause intermodulation products. Typically, the most severe is the third order intermodulation, which is illustrated in Fig. 1. This is a well known problem and the two-tone test is employed to characterize and tag the quality of an RF component. The 3rd order intercept point (IP3), which has an input (IIP3) and output power (OIP3), is the metric that can be found in RF component data sheets.

The growing use of frequency agile software and cognitive radios, Internet of Things (IoT) devices, and RF sensors, as well as the ongoing trend of opening up traditionally licensed and protected spectrum for shared use motivates studying less controllable RF environments and their implications on communications performance. More precisely, since the shift is towards software solutions to compensate for hardware and channel impairments, nonlinearity effects that are externally triggered but affect radio receivers will need to be addressed in an efficient, yet adaptive way.

Recent work has shown that even simple communications systems and receivers suffer from high power blockers [3]. Since simple systems, such as the IoT, will coexist with sophisticated communications transceivers, radars and other spectrum consumers, these need to be protected employing a simple, yet adaptive solution. This paper therefore proposes a flexible data driven design that uses a shallow artificial neural network (ANN) to aid in the removal of the intermodulation distortion (IMD) as part of the demodulation process. We introduce and numerically evaluate two artificial intelligence (AI)-enhanced receivers, where in on case the ANN serves as a IMD canceler and in the other as the demodulator. Our results show that a simple ANN structure can significantly improve the bit error rate (BER) performance of nonlinear receivers with strong adjacent channel blockers and that the performance depends mainly on the receiver characteristics.

The rest of the paper is organized as follows: Section II formulates the problem and discusses the context and the related work. Section III introduces the system model based on well established theory and RF nonlinearity models. Section IV introduces our AI-enhanced receiver designs and configuration principles. Numerical results are provided and analyzed in Section V and conclusions are drawn in Section VI.

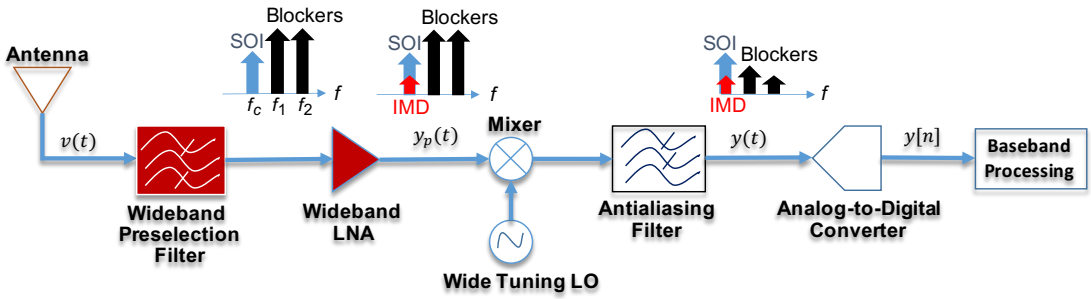

Fig. 1. Receiver with nonlinear RF front end and the spectrum of the signal of interest (SOI), blockers, and intermodulation distortion (IMD) at the different stages of the receiver processing chain. The adjacent channel blockers, but not the IMD, can be eliminated by a conventional digital filter.

II. Problem, Context, and Related Work

A. Problem

In the context of spectrum sharing, where radio systems can operate in different channels and do not know their spectral neighbors a priori, high power signals in adjacent bands can cause nonlinear distortion to the desired signal at the receiver. This is especially true for low-cost receivers which have wide preselection filters and poor, i.e. highly nonlinear, RF front ends, such as typical Wi-Fi or IoT devices. We assume the case where such practical receivers operate in the weak nonlinear region, i.e. where there is no ADC clipping caused by the high-power blockers. The problem is then to design and analyze a simple, yet adaptive digital solution to demodulate the signal of interest in the presence of IMD.

B. Context and Related Work

The nonlinearity problem of components used in communications systems has been studied and different solutions have been proposed in RF and related communications contexts, including fiber optical systems. The power amplifier (PA) is a major source of RF nonlinearity, where too high input signals drive it in its nonlinear operating region. PAs are expensive and inefficient and high linearity comes at a high cost [4]. In order to avoid nonlinear operation, communications transceivers are carefully designed and tuned, and RF spectrum is carefully allocated, defining transmitter masks and considering adjacent frequency allocations. The tuning of communications systems often means that operators make sure to maintain sufficient input power backoff such that the input peaks are still withing the PA's linear operating region. The problem is exaggerated with advanced communications technology, specifically when employing multiple antenna systems where each antenna element has a PA [5]. Digital predistortion is a common method to linearize the output of a PA [6].

Receivers also consume spectrum in the sense that undesired signals that enter the RF processing chain, can distort the receiver and severely compromise its demodulation [3] or sensing performance [7]. Therefore, receivers need to get spectrum allocated and may need guard bands and limited accumulated power levels across the entire band that passes the preselection filter.

The premise of power backoff or careful spectrum regulation cannot be assumed for emerging wireless systems and spectrum regulation. Specifically, cognitive radios can operate in different bands which means that they have to be able to receive signals in a wide range of frequencies. Software radios therefore have wide RF preselection filters, if any. Moreover, spectrum sharing among heterogeneous systems and services can cause high power neighboring signals that enter the receiver. Therefore, transceivers need to dynamically pre-process or post-process signals entering and exiting the nonlinear RF front end.

In [8] an iterative IMD reconstruction has been proposed which outperforms a conventional method that uses least mean squares (LMS) filters to mitigate IMD. This algorithm can handle 5 dB higher adjacent channel interferers when compared with the LMS solution.

The main contribution of this work is that we analyze both high and low IMD effects stemming from high power blockers and moderate to highly nonlinear receivers. Moreover, as mentioned in [8], in contrast to LMS and iterative IMD in which the nonlinear parameter needs to be known, which requires characterizing the receiver, our approach estimates the IMD in real time during operation and removes it. In addition, for algorithms such as LMS, determining the optimum step size is of critical importance to minimize the residual interference.

III. System Model

Receiver nonlinearity has been studied and described by several researchers and the polynomial approximation model is widely used to describe it [9]:

$$r(t) = \alpha_1 x(t) + \alpha_2 [x(t)]^2 + \alpha_3 [x(t)]^3 + ..., \qquad (1)$$

where $x(t)$ is the signal at the input of the nonlinear device and $r(t)$ is the output. Parameter α_i corresponds to the i^{th} order gain (where i = 1, 2, 3, ...) and α_1 is called the linear gain. The third order nonlinearity usually causes the most distortion in the band of interest and the third order approximation is therefore often used [3].

For our system model, the desired signal, or SOI, is at frequency f_c and the adjacent channel blocking signals are at f_1 and f_2 such that $2f_1 - f_2 = f_c$ (as in Fig. 1), or $2f_2 - f_1 = f_c$. The two adjacent channel blockers produce an intermodulation product at the frequency of the SOI when

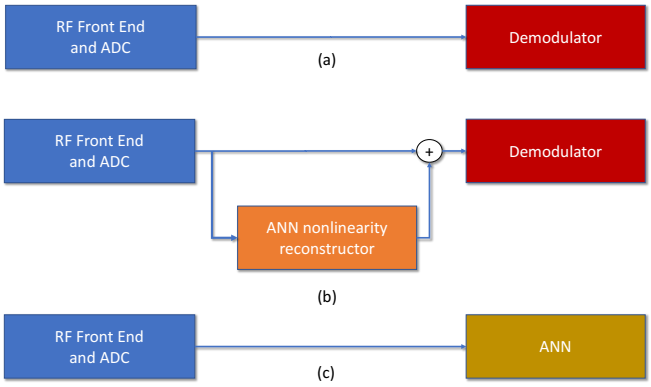

Fig. 2. Conventional receiver (a), ANN-based IMD canceling receiver (b) and ANN-based demodulator (c).

going through the nonlinear device, as shown in Fig. 1. Using (1), the received signal at f_c can then be expressed as [10]

$$r(t) = \alpha_1 s(t) + \frac{3}{2}\alpha_3 [b(t)]^2 c(t)^* + n(t), \tag{2}$$

where $r(t)$ is the signal at the output of the nonlinear device, $s(t)$ is the transmitted signal, the SOI, $b(t)$ and $c(t)$ are the blocking signals, $n(t)$ is the additive white Gaussian noise (AWGN), and α_1 and α_3 are the linear and third order gains.

The third order intercept point, or IP_3, is a measure of RF component nonlinearity. Its input and output values can be obtained from data sheets of performing the two-tone test. The input IP_3 (IIP_3) voltage and power can be calculated as [7], [9], [10]

$$A_{IIP_3} = \sqrt{\frac{4}{3}\left|\frac{\alpha_1}{\alpha_3}\right|} \tag{3}$$

and

$$P_{IIP_3} = 20\log_{10} A_{IIP3} + 10 \text{ [dBm]}, \tag{4}$$

respectively.

IV. AI-Enhanced Practical Receiver

A. AI Models

Existing 4G networks employ all-IP (Internet Protocol) broadband connectivity. AI and its subcategories machine learning and deep learning have been evolving to the point that they will empower fifth-generation (5G) and Beyond 5G wireless networks [11], [12]. Moreover, in order to satisfy the growing demand for wireless connectivity, a new paradigm of wireless communications with the full support of AI is expected to be implemented between 2027 and 2030 [13]. For example, vehicle to everything (V2X) communications can benefit from AI to improve traditional schedulers and congestion control mechanisms and lower the current packet losses for improved safety and comfort [14].

Generally, AI techniques can be categorized as supervised and unsupervised learning. Machine learning and statistical logistic regression techniques, support vector machines (SVM) and artificial neural networks (ANN) are supervised learning techniques. K-means clustering and Q-Learning represent unsupervised learning. There is another approach named semi-supervised learning in which both labeled and unlabeled data exist for training the network.

B. Proposed AI-Enhanced Receiver Designs

The proposed model in this paper is a supervised learning method in which a multilayer perceptron (MLP) ANN with only one hidden layer is designed to extract the information from the nonlinear part of the received signal by labeling the SOI as a target signal in the case where the desired signal is dominant. In contrast, for the case where the power of the interference is stronger than the SOI; by pausing the SOI transmission and just focusing on the nonlinear part of the received signal, the necessary information is extracted by the proposed ANN.

Fig. 2 shows three different receiver models considered in this paper. After the received signal passes the nonlinear front end and is digitized, the first receiver applies the conventional demodulator. This is our baseline receiver. The first proposed AI-enhanced receiver uses an ANN nonlinearity reconstruction block (Fig. 2b). Here the ANN tries to reconstruct the nonlinear part of (2) to subtract it from the output of ADC before applying the conventional demodulation processes. The second proposed AI-receiver designs the ANN to take a distorted input signal and demodulate it. The goal of this receiver is to evaluate whether the ANN can directly extract and demodulate the SOI from the distorted received signal. Our ANN structure is

$$\text{net} = \text{ANN}\{\text{Input}, \text{Target}, \text{LearningAlgorithm}\}. \tag{5}$$

For quadrature modulated symbols, we have two options, work with two ANNs, one for the in-phase (I) and the other for the quadrature (Q) component, or augment the basic ANN structure as follows:

$$net = ANN\{[\Re(In), \Im(In)], [\Re(T), \Im(T)], LA\}, \tag{6}$$

where $\Re(.)$ and $\Im(.)$ stand for the real and imaginary parts, that is, the I and Q components. In, T, and LA represent the input and target signals, and the learning algorithm.

For the problem considered in this paper our basic ANN has one neuron in the input layer and one neuron in the output layer with one hidden layer that has four neurons. The activation function is $tansig$ for the hidden layer and $purelin$ for the output layer. This ANN is used for implementing the ANN canceler (Fig. 2b) and ANN demodulator (Fig. 2c) for a BPSK receiver. The weights are trained as discussed in the next paragraph.

For the QPSK case, since we have both I and Q components, we use 2 input and 2 output neurons for the ANN canceler, with one hidden layer with four neurons and activation functions as before. For the ANN demodulator, we apply one ANN in the I and one in the Q path where each has the same structure as the basic ANN designed for BPSK demodulation.

C. Control Signals and Training

As explained in [15], the MLP tries to minimize the mean square error and fit the curve to the labeled data points. Therefore, for ANN canceler (Fig. 2b), the input to the ANN is the nonlinear component of (2) plus noise, where the learning target is the nonlinear component. In this case, the SOI is absent; that is, the transmitter is turned off. In other words, the SOI pilots are zero. Note that the ANN is not interacting with a pure signal, the nonlinear component of (2) in this case. This makes the training process reliable and practical.

For the ANN demodulator (Fig. 2c), the SOI transmits regular data known to the receiver during the training phase where the target is the SOI. That is, pilots are established as part of the control signaling between transmitter and receiver and are used as the labeled data for training. The trained ANN demodulator then tries to extract the transmitted bits from the SOI which it receives together with the in-band nonlinear distortion and noise.

D. Learning Algorithm

The Bayesian Regularization (BR) algorithm is chosen for training for a few reasons. First, as discussed in [15], the two hyperparameters in a Bayesian Neural Network (BNN) result in utilizing the effective number of weights while training the network. The error is a function of the weights and the hyperparameters α and β:

$$E(w_{MAP}) = \frac{\beta}{2}\sum_{n=1}^{N}\{y(x_n, w_{MAP}) - t_n\}^2 + \frac{\alpha}{2} w_{MAP}^T w_{MAP}. \tag{7}$$

In order to minimize the error function we need to tune the values of parameters α and β. Vector w_{MAP} indicates the posterior distribution of the network weights. Since we are obtaining the initial values for the weights from a normal distribution, some of these weights might be useful during the training at first, but may add error to the system. Therefore, a trained ANN may end up not being fully connected. For more information please refer to [15]

V. Numerical Analysis

The simulator uses complex baseband representation of the transmitted signal. The received signal is the attenuated signal plus the IMD as a result of co-channel blockers and receiver nonlinearity plus AWGN according to (2). The total noise power is set as N = -114 dBW for a bandwidth of $BW = 1$ MHz to account for noise floor elevation due to co-channel interference and receiver noise figure.

We assume that the transmitted and blocker signals all experience an AWGN channel. P, B, and C are the desired and the two blocker signal powers, respectively, at the receiver. The bits of the desired signal and the adjacent channel blockers are produced by independent random sources.

We consider the three receiver implementations from Section IV and shown in Fig. 2: the conventional demodulator, the ANN-based IMD canceler, and the ANN demodulator. We also consider the conventional receiver without nonlinearity in an AWGN channel. The power level of each blocker is set to a high value of 70 dB above the noise floor to evaluate the case of high IMD. We first choose IIP_3 = -10 and -20 dBm to model two types of nonlinear receivers. We then evaluate the performance of the different receivers as a function of the nonlinearity figure between an IIP3 of -30 and +20 dBm, providing a range of practical nonlinear receivers. The SOI and blockers are both assumed to carry data and employ binary and quadrature phase shift keying (BPSK and QPSK) modulation.

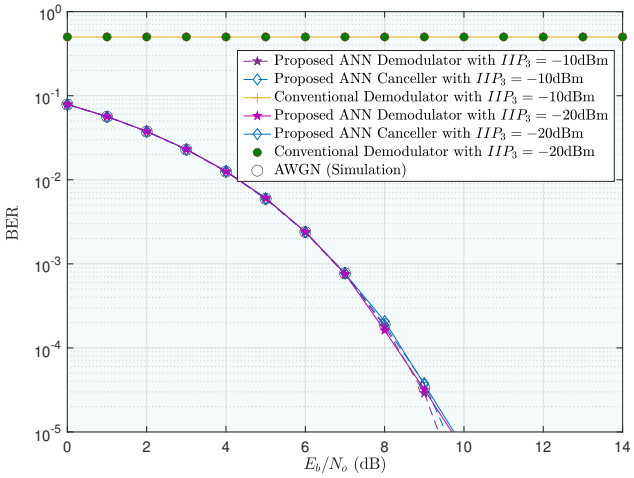

Fig. 3. BER of a BPSK modulated signal with adjacent channel blockers and receiver nonlinearity. The blockers are BPSK modulated signals and are received at 70 dB above the noise floor. The AWGN curve represents the conventional demodulator for an ideal (linear) receiver.

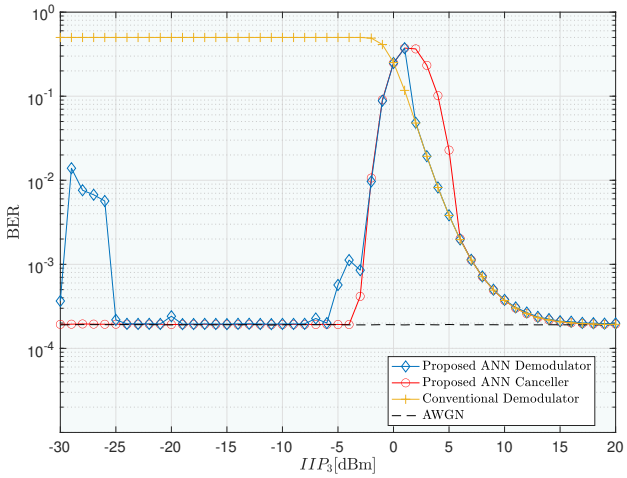

Fig. 4. BER for a BPSK signal for the three nonlinear receivers of Fig. 2 as a function of IIP_3 for E_b/N_0 = 8 dB. The ideal receiver in AWGN channel is shown for reference.

A. BPSK SOI and Blockers for Different IIP_3 Values

Fig. 3 plots the BER of BPSK communications over E_b/N_0 for the different receivers and two IIP3 values with blocker power levels of 70 dB above the noise floor. The conventional demodulator curve shows how the nonlinearity affects and

considerably degrades the BER performance at high blocker power level, even for a BPSK modulation scheme. Also, the figure shows that in general the two proposed ANN models improve the system performance and completely eliminate the effect of the nonlinearity for both IIP3 values, -10 and -20 dBm, which model highly nonlinear receivers. Both AI-enhanced receivers are able to mitigate the IMD and closely match the AWGN lower bound. The ANN canceler slightly outperforms the ANN demodulator at high SNR values.

Fig. 4 compares the BER performances of the three receivers of Fig. 2 for BPSK and an E_b/N_0 of 8 dB as a function of IIP_3 with B = C = N_0 + 70 dB blocker powers. It shows that the conventional demodulator completely fails to extract and demodulate the data from the distorted signal for moderate and highly nonlinear receivers (IIP_3 below 0 dBm), whereas the ANN canceler is able to completely eliminate the severe IMD that otherwise makes the demodulation impossible. The ANN demodulator shows excellent performance, but with some instability for highly nonlinear devices.

The performance gains of the AI-enhanced receivers stem from the fact that high IMD causes the ANN to interact with an almost pure input signal; therefore, by estimating an appropriate function it can fit the curve to the received signal. For low IMD, the AI-enhanced receivers converge to the AWGN benchmark. At intermediate IMD, the proposed cancellation/demodulation techniques behave similar to the conventional receiver.

B. QPSK SOI and Blockers for Different IIP3 Values

Fig. 5 shows the simulation results for QPSK modulated SOI and blockers. We notice that both ANN solutions are able to effectively remove the effect of nonlinearity and match the BER curve of the AWGN system. The increase of dimension from BPSK to QPSK adds a dimension to the ANN input, but the gains of the proposed AI-enhanced receivers do not suffer and their performances still closely match the AWGN lower bound for both receiver types (IIP3 = -10 and -20 dBm).

Fig. 6 shows the performances of the three receivers of Fig. 2 for an E_b/N_0 of 8 dB as a function of IIP_3 with B = C = N_0 + 70 dB blocker powers. These results confirm that for moderate and highly nonlinear receivers, the ANN canceler outperforms the other structures and is able to completely eliminate the severe IMD that otherwise makes the demodulation impossible. So does the ANN demodulator, but we observed outliers which may be due to the initialization of weights during training. Out of 100 ANN instances only few show anomalies and orders of magnitude higher BER which pull the result up, as observed by the three peaks in the ANN demodulator curve at IIP values around -30, -21 and -11 dBm.

The results for IIP_3 between -5 and +5 dBm need to be further analyzed. We call this the medium nonlinear region. What we observe here is that the ANN demodulator performs better in aiding in the demodulation than the ANN canceler. The IMD is less severe here and the ANN canceler has trouble approximating it for removal. The ANN demodulator, on the other hand, which tries to approximate the SOI, is able

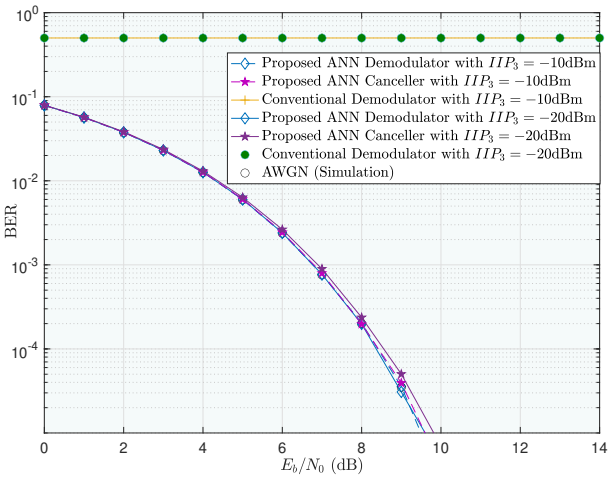

Fig. 5. BER of a QPSK modulated signal with adjacent channel blockers and receiver nonlinearity. The blockers are QPSK modulated signals and are received at 70 dB above the noise floor. The AWGN curve represents the conventional demodulator for an ideal (linear) receiver.

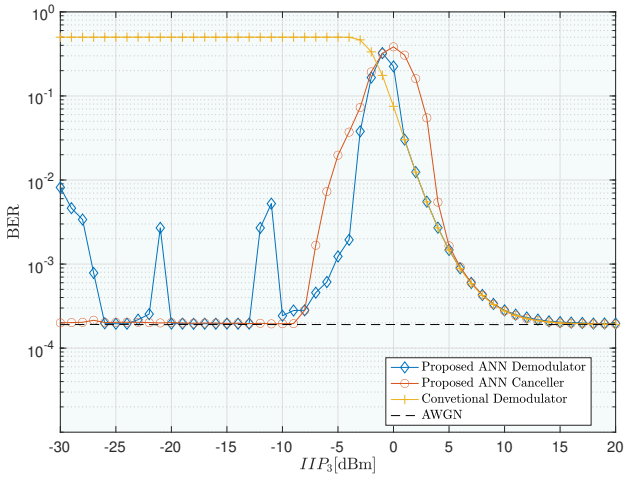

Fig. 6. BER for a QPSK signal for the three nonlinear receivers of Fig. 2 as a function of IIP_3 for E_b/N_0 = 8 dB. The ideal receiver in AWGN channel is shown for reference.

to handle it better and closely approaches the conventional demodulator curve. Where the IMD is low, for receivers with IIP3 of +5 dBm or more, the ANN processing is not needed, but it does not disturb the demodulation process.

The training of the MLP ANN is performed using matrices in MATLAB. This simplifies the derivation of the computational complexity as function of the number of layers and the number of training samples. With t training samples, the order of complexity of operation while propagating from one layer with m nodes to the next layer with n nodes is, $\mathcal{O}(t * m * n)$. Hence, with one input layer with m nodes, one hidden layer with n nodes and one output layer with k nodes, the complexity of proposed ANN receiver for one epoch is, $\mathcal{O}(t * m * n * k)$. Since I epochs are required to train the network, the overall complexity becomes, $\mathcal{O}(t * I * m * n * k)$, which corresponds to the number of matrix multiplications.

In conclusion, our results show that the AI-aided demodulation process is robust. It enables demodulation with severe IMD which is otherwise impossible. For medium IMD levels, the two AI-enhanced receivers perform similar to the regular receiver. For excellent receivers or low blocker powers, where the proposed ANN processing is not needed, it provides the expected demodulation performance. The region of medium IMD needs to be further analyzed. The ANN structure and training can be further optimized for such receivers and operating scenarios.

C. Discussion

In this paper we have designed an ANN with a fixed structure, which is characterized by one hidden layer with four neurons. One compelling solution to improve the design is to consider an adaptive ANN (AANN). The AANN allows defining different ANN structures with different training algorithms. It can adapt itself to observe the defined criteria. For instance, as Fig. 5 shows, the proposed ANN is trained very well by reaching one of the defined parameters; gradient, performance or epoch, then based on the trained network the system is used to aid in the demodulation and establishes a reasonable BER performance. On the other hand, the AANN can define a different constraint, such as having an SNR loss of less than 2 dB. Then the proposed ANN begins to switch between different structures and algorithms, e.g. considering the Stochastic Gradient Descent Momentum (SGDM), with the aim of meeting the aforementioned constraint. Although this approach applies a very high complexity to the system, it ensures that the results are the optimum among a variety of structures.

VI. Conclusions

We have proposed two AI-enhanced receivers to mitigate the effects of the RF nonlinearity of practical systems. Two communications systems have been examined using the proposed methods and the results evaluated against the ideal system and the conventional receiver. The simulation results first show that the conventional receiver cannot demodulate the data with adjacent high-power blockers causing moderate or high IMD due to receiver nonlinearity. A significant performance improvement of the two proposed ANNs—IMD canceler and demodulator—over the conventional receiver is numerically shown when the blocker power levels are high. We conclude that the use of the proposed ANN nonlinearity canceler, which focuses on estimating and removing the IMD caused by high-power blockers, as well as the ANN demodulator can significantly improve the BER performance. The ANN canceler outperforms the ANN demodulator in terms of stability for highly nonlineary receivers and allows communications even in severely nonlinear systems and harsh signaling environments. The ANN demodulator, on the other hand, outperforms the ANN canceler for medium IMD. Both match the conventional receiver performance when the IMD is low or negligible.

This research has shown that employing data-driven processing with ANNs, which can inherently model nonlinear behavior, can effectively help mitigating hardware typical RF impairments. We therefore recommend considering AI controllers for driving future transceivers, both for simple and low-cost IoT devices as well as for sophisticated broadband wireless networks. Research needs to analyze and experimentally verify the applicability of AI and devise suitable structure and their stability for controlling modern broadband waveforms and practical communications systems.

Acknowledgment

This work was supported in part by the National Science Foundation grants CNS-1564148, ECCS-2030291 and CNS-2120442.

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