Research Article

A Novel Autoregressive Spectral Estimation-Based Neural Network Crest Factor Reduction Structure in Power Amplifiers of 5G Systems in Sandstorm Environment

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In this paper, an autoregressive spectral estimation using a multilayered neural network is proposed to reduce the nonlinearities of 5G MIMO power amplifiers and increase the signal-transmitting qualities. The proposed method adopts the two-sided doubly exponential lattice algorithm to achieve the most suitable estimation for in-band compensation. Also, based on the iterative learning control method, a novel crest factor reduction digital predistortion is combined with the multilayered neural network. Based on the results, the proposed algorithm has increased the linearity and stability of the PA performance. The proposed method can improve the robustness of 5G MIMO wireless communication systems.

1. Introduction

A sandstorm is a natural phenomenon where sand particles or dusts are blown from dry and gritty surfaces by gusts of strong winds [1, 2]. These particles travel in the air, increasing PM2.5 rapidly and changing air texture. This phenomenon often exists in arid and sandy areas, such as drylands and deserts. Sandstorms happen fast and can last for several hours or even days. During sandstorms, wireless communication equipments are sometimes heavily affected due to the irregular propagation of the transmitted and received electromagnetic waves [3–5].

5G new radio (NR) systems have used electromagnetic waves with higher frequency to increase data transfer speed and information capacity [6, 7]. Since the frequency of the electromagnetic waves are increased, the wavelength has been decreased to the size that is more comparable to sandstorm particles. Therefore, 5G communication systems are more likely to be affected by this special weather condition. Also, with the development of modern wireless communications, more stringent requirements have been put forward in terms of power efficiency and linearity. Efficiency determines the effectiveness of the DC power converted to radio power while linearity determines the quality of output signal from the power amplifier. However, for high frequencies, especially in the millimeter region, electromagnetic waves tend to decay rapidly in real-time channels. Therefore, massive multiple-input multiple-output (MIMO) has been widely applied in 5G systems, where large scale of antennas, mixers, and power amplifiers have been used [8–13]. With the increase of operating frequencies and bandwidth, it is not easy for power amplifiers to achieve high linearity and power efficiency in the whole band. Nonlinearity can become much worse when a sandstorm takes place. Also, the cross-coupling from adjacent channels often makes the system performance worse. Moreover, the MIMO system is more complicated and consumes more electricity compared with single-channel system. Therefore, MIMO systems face more interferences, where more efficacious methods for linearity correction should be applied. In the operating band, since each frequency wavelengths are different, the electromagnetic waves are not evenly affected by the effects of reflection, interference and diffraction by the dynamically flying sandstorm particles.

In microwave and millimeter wave power amplifiers, digital predistortion (DPD) techniques have often applied [14–16].
DPD has the inverse characteristics of the PA, and it allows PAs to work in their nonlinear region, where the efficiency is pushed to a higher level. The performances of DPD rely heavily on its model and can alleviate nonlinearity and reduce crosstalk in MIMO. For sandstorm weather conditions, the behaviors of nonlinearity become much more unstable and unpredictable. Many different models have been proposed in previous literature, such as Volterra series-based or generalized memory polynomials \cite{17-20}, and dynamic deviation reduction \cite{21,22}. Most of the time, the model is constructed based on the device behavior to mitigate cross-coupling amongst signal channels. Since complexity of MIMO systems is usually high, each channel can use independent DPD. This method is feasible in full beamforming structures, in which each channel has access to the baseband. However, it is not very suitable with hybrid beamforming structures \cite{23-26}. To solve this limitation, \cite{27} has proposed a compromising method, where all power amplifiers of each channel use independent subarrays. In this way, the average error has been reduced largely from the output port. \cite{28,29} have proposed over-the-air (OTA) target linearization technique, where the main lobe of the radiation pattern can be corrected. However, the radiated signals in other directions, for example at side lobes, are not well linearized.

In order to better improve DPD performance, different types of neural network models have been proposed in the fields of radio frequency, microwave and millimeter wave circuits in recent years. Many types of neural networks have also been proposed, distributed spatiotemporal neural networks \cite{30-32}, taking into account the memory effect to reduce the nonlinearity and imbalance of the I/Q channel. Literature \cite{33-35} proposed an iterative control algorithm for training DPD based on neural networks, which can also be applied to MIMO systems. In this way, the crosstalk between different input and output channels can be further reduced. In order to more effectively estimate the coefficients generated by the clipping and bank filtering process, a multilayer hidden NNs DPD method for joint crest factor reduction is proposed in \cite{36-39}. The augmented iterative learning control algorithm is used for signal training, which improves the accuracy of the model. This method can alleviate the limitation of the peak value of the input signal to the average value.

Different types of neural networks can be integrated into the MIMO system to obtain excellent performance in terms of linearization. However, under sandstorm conditions, the sand particles in the air will seriously affect the output signal, leading to in-band fluctuations and rapid deterioration of noise. This process is random and probabilistic. Therefore, the MIMO system still has a lot of room for performance improvement to withstand certain extreme weather conditions. Therefore, in order to improve the stability of the system under certain extreme weather conditions, we have proposed a novel ASE-NN-CFR-DPD algorithm. The algorithm is first preprocessed by ASE and then fed into a dual-channel multilayerly implicit neural network for linearity and stability improvement. As the results show, the proposed algorithm can achieve better in-band flatness and noise suppression in sandstorm weather conditions.

2. MIMO System Analysis

2.1. Analysis of MIMO Systems in Sandstorm Environment.
In MIMO communication systems, antennas with similar patterns are aligned in an array to construct the radiation beam in the air, as shown in Figure 1. Each antenna is connected to a PA and a phase shifter. The PA can amplify the signal to a certain power level to ensure that the signal can travel through the desired distance. By changing the phase delay of each phase shifter, the wave position of strengthening changes, which results in the direction change of the radiated beams. To ensure in-band flatness and reduce noise, the DPD process is integrated into the system to form a closed feedback loop. Normally, the electromagnetic waves travel in clear air conditions, sometimes with rain, snow or even hail. Generally, small water drips either in liquid or solid form do not have much impact on the propagation of the electromagnetic waves in the 5G NR band \cite{6}. In some geological regions, however, sandstorms have been the mainstay weather condition, especially during spring or autumn reason. Sand particles travelling through the wind can affect the electromagnetic waves sharply. When electromagnetic waves pass through the dust storm area, the particles absorb, reflect and scatter the waves, thus causing attenuation. Attenuation is related to particle size, distribution density, and material. Since dust storm particles are dynamically changing in the air, the dynamic effects of electromagnetic waves are also dynamically changing. For L-band and S-band electromagnetic waves, the dynamic attenuation range of electromagnetic waves can reach 1−15 dB/km. Although the probability of sandstorms appearing in many areas is not high, their impact on electromagnetic waves is still quite large. They can reduce the quality of communications and can even malfunction the whole system, causing temporary communication failure. Therefore, 5G MIMO wireless communication systems face more challenges during the sandstorm period compared with working in clear air and fine weather. For example, large particles in the sandstorm affect the lower band more while the small particles have a larger impact on the higher band. Since the distribution of the particles is dynamically random, the in-band root mean square error (RMSE) will be greatly increased. Then, in order for the communication systems to work in more stable conditions, a more adaptive and robust DPD method should be adopted in the regions with whimsical weather conditions.

The full radio wave test of the OTA test can measure far field, compact field, mid field and near field with plane wave generator, etc. For example, the 3GPP standard proposes four options: far field, constricted field, one-dimensional constricted field and near field, and gives suggestions on the test accuracy of different fields and the calibration and test methods of related test items. For the far field, the far-field distance between the DUT and the measurement antenna depends on two factors: the antenna aperture and the wavelength. At such a large test distance, path loss becomes a key issue. If it is guaranteed that the dynamic range and index requirements of the spectrum analyzer and signal
source are still met after the attenuation through the path, the test can be carried out normally. Although there is a large path loss, the advantages of the far field are also obvious. First of all, in terms of frequency, due to the advantages of large space and simple test structure, the low frequency can be easier to achieve very low than other fields, and the high frequency can also be as high as dozens of GHz. It is also an ideal place for antenna pattern testing, cell coverage, multibeam testing, and temperature testing. The test system can test the beamforming pattern and EIRP (effective isotropic radiated power), EVM (error vector magnitude), occupied bandwidth, EIS (effective isotropic sensitive, effective), and omnidirectional sensitivity of the 5G base station antenna.

Based on our calculation and our input signal dynamic results, we will later show that the in-band and out-of-band noise have been increased since winds and sand particles are dynamically flowing. Also, the flatness of in-band properties has been compromised since the reflective and absorptive rates at different frequencies are also different if the medium is inhomogeneous. Therefore, the properties of the electromagnetic waves in the sandy region are characterized by the refractive index in the region. Also, the mixed refractive index is directly determined by the distributions of the sand particles in the blowing wind. Then, the change in particle distribution and size can affect the in-band behavior of the communication channels.

2.2. Analysis of the ASE-NN-DPD Model. Figure 2 shows the block diagram of the classic DPD process and the proposed DPD process. In the classic model, the input signal is delayed and advanced, and they are separated into the real parts and imaginary parts. Then, the signal points are fed into the neural network, and then, the output signal is combined with the processed real parts and the imaginary parts. The classic DPD method shows relatively weak corrective effects against strong sandstorm weather conditions. Inspired by the lattice filter-based multivariate autoregressive spectral estimation proposed in [40], and the augmented iterative learning control-based neural network proposed in [41], we have proposed a new DPD method. Two major modifications have been made to the classic DPD process. First, the delay and advance module has been replaced by the ASE process. Then, the neural network is replaced by the NN-CFR module.

For an n-dimensional signal \( x(t) \),

\[
x(t) = [x_1(t), \ldots, x_m(t)]^T, \quad t \in \mathbb{Z}.
\]

The \( n \)th order vector autoregressive formula can be given as

\[
x(t) = \sum_{i=1}^{n} B_{i,n} x(t-i) + n_n(t),
\]

where the covariance of \( n_n(t) \) is

\[
\text{cov}[n_n(t)] = \sigma^2_{n_n}.
\]

We denote

\[
\beta_n = \text{vec}\left\{B_{1,n} \cdots B_{n,n}\right\}^T,
\]

and

\[
y_n(t) = [x^T(t-1), \ldots, x^T(t-n)]^T.
\]
Then, equation (2) can be written in the following notation:

$$\mathbf{x}(t) = \mathbf{c}_n^T(t)\mathbf{\beta}_n + \mathbf{n}_n(t),$$

where

$$\mathbf{c}_n^T(t) = [\mathbf{I}_m \otimes y_n(t)]^T.$$  (7)

We define

$$\mathbf{B}_n(z, \mathbf{\beta}_n(t)) = \mathbf{I}_m - \sum_{i=1}^n \mathbf{B}_i(t)z^{-i}. $$

(8)

Then, the instantaneous spectral density function can be calculated as

$$S_n(\omega, t) = \mathbf{B}^{-1}\left[e^{i\omega}, \mathbf{\beta}_n(t)\right]\sigma_n(\mathbf{B}^{-1}\left[e^{-i\omega}, \mathbf{\beta}_n(t)\right].$$

(9)

The dynamic ASE process consists of four steps. The first step is to evaluate the reflection coefficients. This step can be achieved using the exponentially weighted lattice algorithm, where the reflection coefficients can be estimated as

$$\mathbf{Q}_{n|k}(t) = F[\mathbf{c}^-_{n-1|k}(t), \mathbf{Q}^-_{n|k}(t \pm 1), \mathbf{n}_{n-1}(t \pm 1)]$$

$$\mathbf{F}(\mathbf{x}, \mathbf{Y}, \mathbf{z}) = (\mathbf{I}_m - \mathbf{xx}^T)^{1/2}\mathbf{Y}(\mathbf{I}_m - \mathbf{zz}^T)^{1/2} + \mathbf{zx}^T,$$

(10)

where

$$\mathbf{Q}^+_{n|k}(t) = [\mathbf{R}^+_{0|k}(t), \mathbf{R}^+_{1|k}(t), \ldots, \mathbf{R}^+_{N|k}(t)]$$

for $t \in [1, T_0]$.  (11)

Also, $\mathbf{Q}$ and $\mathbf{R}$ stand for the $Q$-parametrization and the $R$-parametrization respectively. $\mathbf{F}$ is the transformatory matrix function. The stable condition of VAR models can be unconditionally satisfied by the obtained reflection coefficients. The second step is to evaluate the autocorrelation coefficients. This step can be achieved using the order-recursive algorithm, where the $R$-parametrization can be given as

$$\mathbf{R}^+_{n|k}(t) = \{\mathbf{R}^+_{0|k}(t), \mathbf{R}^+_{1|k}(t), \ldots, \mathbf{R}^+_{N|k}(t)\}$$

for $t \in [1, T_0]$.  (12)

Also, the model fusion matrix with the estimated autocorrelation coefficients can be calculated as

$$\mathbf{W}^+_{n|k}(t) = \begin{bmatrix} \mathbf{R}^+_{0|k}(t) & \mathbf{R}^+_{1|k}(t) & \cdots & \mathbf{R}^+_{N|k}(t) \\ \vdots & \ddots & \ddots & \mathbf{R}^+_{1|k}(t) \\ \mathbf{R}^+_{n|k}(t) & \cdots & \mathbf{R}^+_{1|k}(t) & \mathbf{R}^+_{0|k}(t) \end{bmatrix}$$

(13)

The third step is to fuse the model. This step is to realize two-sided parameter estimation by combining the forward and backward EWLMF algorithms. In this step, the Yule–Walker equations can be solved with the order-recursive Whittle–Wiggins–Robinson algorithm. The final step is to select the best fitting model. The model with the minimum average multivariate final prediction error is chosen as the desired model. Therefore, the spectrum density function can be estimated using relative entropy rate (RER)

$$d_{\text{RER}}(t) = \frac{1}{4\pi} \left[ \frac{\pi}{-\pi} \text{tr}\left[\mathbf{S}_n(\omega, t) - \mathbf{S}_n(\omega, t)\mathbf{S}_n^{-1}(\omega, t)\right] - \log \det\left[\mathbf{S}_n(\omega, t)\mathbf{S}_n^{-1}(\omega, t)\right] \right] d\omega.$$  (14)

Then, the signal can be preprocessed with clip-and-filter (CAF). This process consists of two steps. The first step is to clip the signal input with a threshold $T$ for correction, which can be calculated as

![Figure 2: The block diagram of the DPD process with the proposed model.](image)
3.1. The Linearity Improvement of PAs. In our simulation, two typical behavior models of PAs have been used, as shown in Figure 4. The power amplifier is designed using a commercial 10W CGH40010F packaged GaN transistor of Cree, with an operating frequency from 1.75 to 1.95 GHz. The substrate is Taconic RF-35 with a permittivity of 3.5, loss tangent of 0.0018, and thickness of 0.508 mm. The carrier amplifier is biased in deep class AB with a quiescent current of 50 mA and a drain voltage of 28 V. The peaking amplifier is biased in class C with a gate voltage of −7.5 V and drain voltage of 28 V [13]. The measurement is achieved through the WebLab system. The measurement instruments that are used in the WebLab are from Rohde & Schwarz. For the signal generation, an R&S SMW200A and FSW26 are used for the analysis. Both instruments have options for the generation and analysis of signals. The PA that acts as the DUT is the Doherty PA with an operating frequency of 1.85 GHz. The IQ signal is the baseband signal from the workstation and is fed through the vector signal transceiver. The sampling frequency is 200 MHz and the bias voltage is 5 V. The vector signal transceiver upconverts the baseband signal to the carrier frequency of 1.85 GHz. Then, at the output of the PA, the signal is downconverted to a baseband signal with a relative bandwidth of 40 MHz. The first model works in a nonlinear region to ensure high power efficiency. Therefore, it can be seen that the AM/AM characteristic is slightly higher than the anticipated linear line. The AM/PM is also distorted with the increase of the amplitude of the input signal. Due to the environmental noise, the AM/PM at low input amplitude is more randomly distributed. The second model works in a more saturated region. With the increased amplitude of the input signal, the PA cannot ensure its amplifying rate and the AM/AM characteristic is distorted over a certain input signal amplitude. After applying conventional DPD, the AM/AM and AM/PM have been compensated and linearity has been improved. However, the AM/PM characteristic is still unstable at low input amplitude. For comparison, we also have applied the proposed DPD, and it can be seen that AM/AM and AM/PM have further been improved.

3.2. The AILC Performance. With different AILC at noiseless channels, the corresponding PA output can be obtained and their spectra have been given in Figure 5. In this case, we have adopted the proposed algorithm in comparison with the method proposed in [41]. In our simulation, the sidelobe is set at 100 dB, and the side NPSD can reach about −80 dBc. It can be seen that the proposed method can achieve excellent spectral performances of the PA model in the low noise channel.

3.3. The NPSD Performance under Different Scales of Sandstorms. When the air is mixed with sand particles that are blown up by the wind, because these sand particles can reflect and diffract electromagnetic waves propagating through the area, the transmission attenuation increases. Generally, if resonance does not occur, higher frequency waves will experience relatively greater attenuation. Figure 6 shows the normalized power spectral density (NPSD) characteristics of the dust storm area. The in-band NPSD of the signal has been reduced from −0.32 dB to −2.95 dB. In addition, RMSE has also increased. In order to stabilize the in-band characteristics, we applied the proposed ASE-NN-CFR algorithm in this system. We also applied the method proposed in [41] for comparison. It can be seen from the
results that the in-band flatness has been improved and the noise has been suppressed. The in-band flatness error has been reduced from 0.52 dB to 0.12 dB. The performance of this method in terms of flatness error is improved by 29%. The in-band noise has been reduced from 0.134 dB to 0.072 dB. This method improves 13% in reducing in-band noise.

As the wind increases, more sand particles are blown into the air, and the air becomes a more uneven medium for electromagnetic waves. Therefore, higher frequency electromagnetic waves will experience more attenuation. In this
case, the NPSD characteristics are shown in Figure 7. It can be seen that the in-band NPSD drops from −5.24 dB at −18 MHz frequency offset to −5.92 dB at 18 MHz frequency offset. After applying ASE-NN-CFR, the in-band flatness of this method is improved from 0.86 dB to 0.39 dB. The RMSE value has dropped from 0.323 dB to 0.117 dB. Since our proposed algorithm pre-estimates the in-band characteristics, the in-band flatness has been significantly improved. In addition, in-band noise has been gently suppressed. The results show that the algorithm has better DPD performance under moderate dust storm conditions.

In this case, as the wind further increases, some larger sand particles are blown into the air. Since the resonance wavelength is related to the particle diameter, a resonance point can be generated in the NPSD within the band, which results in higher signal attenuation at certain frequency points in the band. The NPSD parameters of the sandstorm area are shown in Figure 8. Compared with the breeze, the NPSD characteristic satisfies a higher in-band attenuation, which leads to resonance caused by larger sand particles, which leads to increased fluctuations. Therefore, from −18 MHz to −7 MHz frequency offset, NPSD decreases sharply as the frequency increases. The compensated NPSD is also given. The in-band flatness is improved from 1.69 dB to 0.92 dB. For in-band noise, the proposed ASE-NN-CFR has a better noise suppression effect. For the proposed method, the in-band RMSE has been further reduced from 0.468 dB to 0.162 dB. The results show that the algorithm has better DPD performance under the conditions of strong sand and dust storms.

The performance comparison has been shown in Table 1. The proposed ASE-NN-CFR algorithm shows better performances in in-band flatness improvement and noise suppression under various sandstorm weather conditions with different wind and sand particle density levels. The limitations and drawbacks of the proposed method are that the linearity effect is still not ideal, especially during strong windstorm conditions. The ideal condition of NPSD is a straight flat line with no fluctuation or attenuation through the working frequency domain. Therefore, there is still much room for improvement for the proposed algorithm in terms of linearity and noise suppression.

4. Conclusion

In this paper, we have proposed a novel ASE-NN-CFR-DPD algorithm to increase the linearity and robustness of modern 5G MIMO communication systems. The proposed algorithm incorporates ASE with multilayered neural networks to stabilize the signal channel of the PAs. As compared with some other recently published algorithms, the proposed algorithm can achieve a higher noise reduction level and better in-band flatness. The proposed algorithm can be applied in 5G MIMO communication systems in worse weather conditions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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