REMOTE SATELLITE AMPLIFIER PREDISTORTION USING THE INDIRECT LEARNING ARCHITECTURE

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I. ABSTRACT

Abstract—Power amplifiers (PAs), an integral component to most wireless communication systems, are inherently nonlinear devices that introduce out-of-band spectral intermodulation to the amplifier output, which can exceed regulatory limits. One solution is to operate the PA in a highly backed-off state to achieve quasi-linear performance. Operating in this region requires a higher-saturated power rating for a given output power and reduces DC-to-RF efficiency. A more effective, low-cost solution is to apply digital predistortion which pre-compensates for the harmful nonlinear effects. A common framework for identifying the predistortion system is known as the indirect learning architecture. Typically this predistortion architecture is applied to accessible ground-based systems, i.e. a cell base station or wireless repeater. The objective of this study was to develop an architecture to apply predistortion remotely to inaccessible PAs on-board orbiting communication satellite systems, such as the NASA developed Tracking and Data Relay Satellite System (TDRSS). Several complications arise when attempting predistortion remotely including uplink/downlink additive noise, signal accessibility, and time-varying satellite round-trip delay which are not encountered when predistorting accessible amplifiers. Several techniques are introduced and simulated to resolve these unique challenges to remote predistortion.

II. INTRODUCTION

Power amplifiers (PAs) operated in their most efficient regime, near saturation, are nonlinear producing amplitude-to-amplitude modulation (AM-AM) conversion as well as amplitude-to-phase modulation (AM-PM) conversion of a narrowband signal. These effects have been known for many years in the context of traveling-wave tube (TWT) amplifiers, a common type of amplifier used in satellite communication. The nonlinearity induces several harmful effects, including intermodulation in multicarrier environments, and spectral regrowth in single-carrier settings. Out-of-band spectral power can then increase to the point of not meeting regulatory specifications. Moreover, the in-band distortion produces degradation in bit error rates (BER) relative to that of linear amplifiers.

Newer satellite transmission standards, such as digital video broadcasting - satellite - second generation (DVB-S2) that use higher order modulation schemes are increasingly vulnerable to these nonlinearities because of their high peak-to-average ratios. Complicating matters, PAs exhibit memory effects where the output not only depends on the current input, but also on the magnitude of previous values of the input, producing additional distortion. To meet frequency mask requirements of regulatory agencies and bit-error rate (BER) performance requirements of customers, many satellite system operators are being driven to confront the effects of nonlinear power amplifiers.

One solution is to backoff the amplifier, i.e. reduce the drive level so that operation is more confined to the quasi-linear range of amplification. The disadvantages of this approach are two-fold: 1) a higher saturated power rating is needed to achieve a given desired linear power output, and 2) the DC-to-RF power efficiency suffers greatly.

The technique of digital predistortion employs an approximate inverse nonlinearity ahead of the power amplifier, at a low level, such that the cascade operation is close to ideal, i.e. the output amplitude is just some constant $G$ times the input amplitude, and phase at the output is the same as that of the input. The earliest predistorters were analog devices with RF feedback, which were difficult to align, prone to instability, and seldom performed well. More recently, digital signal processing (DSP) technology has been applied, along with adaptive training of the predistorter, to achieve substantial...
improvement in the linearization task. These systems act on a baseband I/Q discrete-time version of the input signal (hence the common name digital predistorter), producing a precompensated I/Q waveform that is converted to continuous-time, up-converted, and amplified by the PA.

A. Applicability to NASA mission

The Tracking and Data Relay Satellite System (TDRSS), developed by NASA, relays mission and tracking data through nine operational satellites (with two currently under development) to/from orbiting user satellites including the Space Shuttle, the Hubble Telescope, and the International Space Station. Figure 1 shows the Tracking and Data Relay Satellite (TDRS) spacecrafts relaying user satellite data to a ground-station. Each relay satellite incorporates multiple inherently nonlinear traveling wave tube (TWT) power amplifiers that require severe input power backoff, which limits output power and amplifier efficiency. A high order modulation scheme, such as 16-point quadrature amplitude modulation (16-QAM) recently proposed for TDRSS in [8], is especially vulnerable to the PA nonlinearities.

A robust digital predistortion technique along with a field-programmable gate array (FPGA) implementation can linearize the power amplifiers and significantly enhance TDRSS communication. Aside from application to TDRSS, other NASA communication systems such as the Deep Space Network, which connects with current science missions on Mars and those spacecraft passing other planets, would significantly benefit from using linearized power amplifiers.

B. Indirect Learning Architecture

The indirect learning architecture (ILA) introduced by Eun and Powers, shown in Fig. 2, is a commonly selected architecture for identifying the predistorter [2]. This architecture begins by training an inverse for the PA in the block labeled ‘Predistorter Training (A)’ following the PA in a post-inverse configuration. Note as the initial training begins that the predistorter block labeled ‘Predistorter (Copy of A)’ equals an identity element such that \( z(n) = x(n) \). The training block has a scaled version of the PA output \( y(n)/G \) as its input, where \( G \) is the desired gain of the linearized PA. A nonlinear model with memory, e.g. memory polynomial model, is adopted for the predistorter training block which has as its output \( \hat{z}(n) \). Then, an adopted algorithm, e.g. least-squares, attempts to drive error \( e(n) \) to near zero such that \( \hat{z}(n) \approx z(n) \). This procedure creates an approximate post-inverse for the PA.

The next step is to commute the order of the post-inverse and the PA by shifting the post-inverse to a position preceding the PA. This is achieved by copying the post-inverse coefficients to the predistorter, using it as a pre-inverse. The commutation of nonlinear systems, such that the tandem response is unchanged, is possible only when the post-inverse is an exact inverse, i.e. the error signal is zero. Here the postinverse system is an approximate inverse for the PA, thus we can only expect the tandem response to be approximately the same when the order swapped. Most literature to date regarding the ILA suggests only a single commutation [2],[3],[4]. Experimental results however show that iterating this procedure, i.e. identifying a post-inverse, copy the coefficients to the predistorter, and repeating, improves performance as measured by waveform distortion, adjacent channel intermodulation, and demodulator constellation quality to exceed the one-step approach. This iterative approach has been shown to converge experimentally after a few iterations.

C. Modeling nonlinear systems with memory

The simplest model for a nonlinear PA is a memoryless nonlinear model, typified by models of Saleh [5] for example. It is now known, however, that memory effects need to be incorporated into PA models (and predistorters), at least for wideband operation, in order to achieve high performance. The general Volterra series,
has been well-studied for modeling nonlinear systems with memory [1],[9]. The primary disadvantage of modeling the predistorter based on the Volterra series is the number of coefficients needed, perhaps 100’s, depending on model order and memory, and the corresponding complexity of implementing the predistorter in hardware.

A less-complex, special case of the more general Volterra series, called the memory polynomial has the following form with order \( K \) and memory \( Q + 1 \) where the coefficients \( a_{kq} \) are complex. If we were modeling a PA with the memory polynomial, the discrete time PA input would be denoted by \( z(n) \) and PA output by \( y(n) \). These analytic models used for PAs can also be employed for predistorters.

\[
y(n) = \sum_{k=1}^{K} \sum_{q=0}^{Q} a_{kq} z(n-q) |z(n-q)|^{k-1} \tag{1}
\]

### III. Remote Predistortion Architectures Using Indirect Learning

Predistortion techniques to date have been based on the concept that predistortion will be added to an accessible PA system, as is common for ground-based PA systems, i.e. cell base stations or wireless repeaters. A different architecture, a modified remote version of predistortion, was developed for applying predistortion to satellite systems remotely, as there are many nonlinear satellite PAs in orbit that could benefit significantly from predistortion. In addition to the challenges of applying predistortion to accessible PAs, there are four additional complicating factors associated with applying predistortion remotely: 1) the time-varying, long uplink and downlink delays to/from the satellite, 2) the physical separation of the PA from the predistorter and the associated signal access problem 3) uplink and downlink additive white Gaussian noise (AWGN), and 4) limits on out-of-band spectral emissions of the predistorted satellite uplink signal.

To better understand the impact of these complications and how we might address them, we introduce two different cases, a monostatic case and a bistatic case using Fig. 3. In the monostatic case, the transmitting ground-station is assumed to have access to the signal broadcast by satellite, i.e. the ground-station is within the antenna beamwidth of the satellite transmission and is thus capable of receiving the signal it just sent to the satellite. In the bistatic case, the transmitting ground-station is not assumed to have access to the satellite broadcast. In this case, we will assume to have some access to the user terminal. The user terminal can be another ground-station, as pictured, or another orbiting satellite, i.e. the International Space Station.

An architecture, a modified remote version of a PA with the memory polynomial, the discrete time PA input would be denoted by \( x(n) \) and PA output by \( y(n) \) using Fig. 4 based on the indirect learning architecture previously described. Differing from the typical indirect learning, there are two PAs in the loop, \( g_1(\cdot) \) and \( g_2(\cdot) \), which are the ground-station based PA and the relay satellite PA respectively. One can form the composite nonlinearity, \( h(z(n)) = g_2(g_1(z(n-D_1)) \cdot \alpha_1) \) where \( D_1 \) and \( \alpha_1 \) are uplink delay and attenuation respectively, and treat the two PAs as if they were one system. Remote predistortion will attempt to compensate for the tandem nonlinearity. The downlink will incur both delay, \( D_2 \), and attenuation, \( \alpha_2 \), as indicated in the diagram. Not included in the diagram, the uplink and the downlink receiver will also introduce noise, which will be addressed in a subsequent section.

Since the receiver is collocated with the transmitter, we have access to the precompensated signal \( z(n) \) and the received signal \( y(n-D_2) \) at the ground-station. The time delay needed to align the precompensated signal with the received signal, as required by the indirect learning, can be calculated using basic cross-correlation techniques to estimate total delay incurred on the uplink and downlink, \( D = D_1 + D_2 \). As each TDRS spacecraft is in geostationary orbit, the amount of delay should not vary rapidly as it would with a low-earth orbit system. The predistorted waveform \( z(n) \) must be stored in a (potentially large) first-in first-out (FIFO) buffer.

To identify the predistorter, we begin by adopting the memory polynomial structure for the predistorter. We will assume the system only includes odd-order terms, as is standard in the literature. The predistorter can be described by

\[
z(n) = \sum_{k=1}^{K} \sum_{q=0}^{Q} a_{kq} x(n-q) |x(n-q)|^{k-1} \tag{2}
\]

where we have order \( K \), memory \( Q + 1 \), and the coefficients \( a_{kq} \) are complex.

Fig. 3. Satellite uplink and downlink

\[\text{delay} = 1/8 \text{sec}\]

\[14 \text{GHz}\]

\[12 \text{GHz}\]
Accordingly, the block labeled 'Predistortion Training (A),' a.k.a. the post-inverse, shown in Fig. 4 can be described by:

\[
\tilde{z}(n-D) = \sum_{k=1}^{K} \sum_{q=0}^{Q} a_{kq} \frac{y(n-q-D_2)}{G} y(n-q-D_2) \cdot \frac{k-1}{k} \tag{3}
\]

where \( G = G_1a_1G_2a_2 \) is the overall link gain, with \( G_1 \) and \( G_2 \) being the linearized gain of the ground-based and relay satellite PAs respectively.

Since output \( \tilde{z}(n) \) is linear in the coefficients \( a_{kq} \), we can use the batch least-squares algorithm to identify the coefficients. With this in mind we introduce the new sequence

\[
u_{kq} = \frac{y(n-q-D_2)}{G} y(n-q-D_2) \cdot \frac{k-1}{k} \tag{4}\]

and it is desired that we would have

\[z = Ua\tag{5}\]

where \( z = [z(1-D), \ldots, z(N-D)]^T, U = [u_{10}, \ldots, u_{1K_Q}, \ldots, u_{1Q}, \ldots, u_{KQ}], u_{kq} = [u_{k,q}(1), \ldots, u_{k,q}(N)]^T, \text{ and } a = [a_{10}, \ldots, a_{KQ}, \ldots, a_{1Q}, \ldots, a_{KQ}]^T, \text{ where } (-)^T \text{ denotes transpose.} \) Then, the least-squares solution to (5) is the following where \((-)^H \text{ denotes conjugate transpose.}\)

\[\hat{a} = (U^H U)^{-1} U^H z\tag{6}\]

Using the iterative approach, the batch least-squares procedure is completed and the identified coefficient vector \( \hat{a} \) is copied to the predistorter once each iteration until convergence.

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**B. Bistatic Predistortion Architecture**

For the bistatic case, we introduce another block diagram for remote predistortion in Fig. 5, again based on the indirect learning architecture. By assumption in the bistatic case, the transmitting ground-station does not have access to the precompensated signal \( z(n) \). This signal plays an essential role in the indirect learning architecture and thus we desire to mimic this predistorted signal at the receiving ground-station. Using the processing branch shown in Fig. 5, the received signal \( y(n-D_2) \) is demodulated and decisions are made, giving an estimate of the original input bits, \( d_n \). These bits are remodulated and predistortion is applied, initially a unity operation, to produce an exact copy of the predistorted signal, \( \tilde{z}(n) \), if no decision errors are made. Note that when using a sufficiently large batch size that a small number decision errors spread throughout the batch are initially tolerable. Any decision errors here are a nuisance that will decrease with the increasing linearity of the PA.

Though this is more complex than a typical implementation of the indirect learning architecture, it is important to note that this approach will concentrate all of the computation on the ground, which is consistent with the TDRSS system emphasis of processing on the ground to simplify the inaccessible satellite. Additionally, with the predistorted signal being generated at the receiving ground-station, we are able to circumvent the time-varying uplink/downlink satellite delay encountered in the monostatic case, hence a FIFO buffer is not required in this case.

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**Fig. 4. Monostatic remote digital predistortion block diagram**

**Fig. 5. Bistatic remote digital predistortion block diagram**
\[ \hat{z}(n) = \sum_{k=1}^{K} \sum_{q=0}^{Q} a_{kq} y(n-q) |y(n-q)|^{k-1} \] (7)

where delay is omitted since, as previously mentioned, a new reference signal will be generated at the ground-station.

Since output \( \hat{z}(n) \) is linear in the coefficients \( a_{kq}, \) we can again use the batch least-squares solution to identify the coefficients. We introduce the sequence

\[ u_{kq} = y(n-q) |y(n-q)|^{k-1} \] (8)

and it is desired that we would have

\[ \tilde{z} = U \hat{a} \] (9)

where \( \tilde{z} = [\hat{z}(1), \cdots, \hat{z}(N)]^T, \) \( U = [u_{10}, \cdots, u_{K0}, \cdots, u_{1Q}, \cdots, u_{KQ}], \) \( u_{KQ} = [a_{KQ}(1), \cdots, a_{KQ}(N)]^T, \) and \( a = [a_{10}, \cdots, a_{K0}, \cdots, a_{1Q}, \cdots, a_{KQ}]^T. \) The least-squares solution for (9) is

\[ \hat{a} = (U^H U)^{-1} U^H \tilde{z}. \] (10)

As before, when using the iterative approach, the identified coefficient vector \( \hat{a} \) is copied to the predistorter once each iteration until a solution converges.

**IV. REDUCING THE EFFECT OF NOISE**

Though not explicitly annotated in Figs. 4 or 5, the PA input and output are real signals modulated at a RF carrier frequency. RF receivers (not shown), located on the relay-satellite and at the ground-station, introduce additive white Gaussian noise (AWGN) to the received signal. We will refer to noise introduced at the relay-satellite receiver as uplink noise \( n_1 \) and noise introduced at the ground-station receiver as downlink noise \( n_2. \) The effects of AWGN and a proposed technique to overcome this can be applied to both the monostatic and bistatic cases.

Interestingly, AWGN affects predistortion performance even under the standard indirect learning architecture, that is, noise is introduced in the local receiver portion of the indirect architecture. Morgan et.al. in [7] shows that AWGN added by the local receiver introduces a bias to the coefficients. A forward modeling technique is proposed and has been adapted here for remote predistortion.

This approach, diagrammed in Fig. 6, adds one step to the architecture, that is, first a model of cascaded PAs is trained, perhaps using a similar least-squares procedure as described previously, such that its output \( \hat{y}(n) \) approximately equals the PA output \( y(n). \) The least-squares approach used for training the approximate PA model can, with a sufficiently large batch-size, “average out” the noise. Then using the approximate PA model output, \( \hat{y}(n), \) in place of the noisy received PA output, the indirect learning architecture proceeds normally to produce predistortion coefficients. Note that when noise is present, the coefficients will not be truly unbiased, but we can expect to reduce the bias by increasing the block length used in the least squares solution of the forward model. Without the forward modeling, we could not expect that increasing the block length of the inverse modeling would reduce the coefficient bias.

**V. REDUCING UPLINK ADJACENT CHANNEL INTERMODULATION**

When predistortion is applied locally to an accessible PA, the predistorted signal \( z(n) \) shown in Fig. 2 is not radiated, that is, only the PA output \( y(n) \) is radiated. However, in the monostatic and bistatic remote approaches, the predistorted signal and the PA output are both radiated. Fig. 7 displays the spectral characteristics of an example predistorted signal (a) and the corresponding PA output signal (c). Notice that while the compensated PA output spectrum is nearly identical to the input signal, as desired, the predistorted signal spectrum is poor. In fact, it is worse than the spectral characteristics of uncompensated PA output (b), potentially not meeting regulated frequency mask specifications. Nonetheless, when the poor spectral characteristics of the predistorted signal combine with the effects of the nonlinear PA, a signal with improved spectral characteristics is produced. Still, it is important to recognize that while the spectrum of the PA output

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(the downlink) is subject to regulation, the spectrum of the predistorted signal (the uplink) is also subject to regulation when using remote predistortion.

Two alternatives to the basic indirect learning architecture are introduced, 1) prefiltering the inverse and 2) dual inverses, each of which establish a balance between the out-of-band power of the uplink and downlink signals. Note here that noise and delay were not included to allow for focus on the basic performance differences of the two techniques.

The first technique we will refer to as “prefiltering the inverse,” displayed in Fig. 8, includes a low-pass filter prior to the post-inverse, labeled ‘Predistorter Training A.’ This filter reduces the out-of-band power inherent to the uncompensated PA output that is “seen” by the post-inverse block. The post-inverse is trained using similar techniques to those described in the previous sections. Though here, the post-inverse is trained using a filtered version of the PA output, $y_f(n)$. Consequently, the post-inverse will not correct for as much out-of-band error. In turn, the resulting predistorter does not produce as much out-of-band correction. The net effect reduces the out-of-band power of the predistorted signal as desired. The pass-band to stop-band ratio of the low-pass filter, $H(z)$ can adjust the compromise between uplink and downlink out-of-band power.

The second technique we refer to as “dual inverses,” shown in Fig. 9, incorporates two post-inverses. Each post-inverse can be trained simultaneously using techniques previously described. The coefficient vectors, $\hat{a}$ and $\hat{b}$, are copied to their respective predistorter where the predistorted waveforms are linearly combined, according to ratio $\alpha$, to form a composite predistorted signal $z(n)$. The two predistorter training branches, labeled A and B, identify a post-inverse independently. By design, branch A will identify a nonlinear post-inverse while simultaneously branch B identifies a linear inverse.

The output of non-linear predistorter A will appear similar to (a) of the results in Fig. 7 with high out-of-band power as it contains intermodulation components. However, the output of the linear predistorter B will not contain intermodulation components and thus its out-of-band power should be low and similar to the original input (d). With $\alpha$ equal to 1, we would expect good downlink out-of-band power but poor uplink out-of-band power. Conversely, with $\alpha$ equal to 0, we would expect poor downlink but a good uplink spectrum. Therefore, by adjusting the value of $\alpha$ we can adjust linear combination of these two signals and adjust the compromise between uplink and downlink out-of-band power.
VI. Simulations

In this section, we present simulation results of the techniques outlined. Two baseband PAs models were adopted. The relay-satellite PA model is a memoryless model based on a least-squares fit to the nonlinear AM-AM and AM-PM characteristics of the TDRS TWT amplifier in [8]. The PA is modeled by

\[ y(n) = \sum_{k=1}^{K} a_k u(n) |u(n)|^{k-1} \]  

(11)

where \( u(n) \) and \( y(n) \) are in the input and output respectively with the following coefficients.

\[ a_1 = 0.9518 + 0.3068j \]
\[ a_3 = -3.337 \times 10^{-3} - 1.397 \times 10^{-4}j \]
\[ a_5 = 2.959 \times 10^{-6} - 5.929 \times 10^{-8}j \]  

(12)

The other ground-station or user-satellite based PA model incorporated both memory and nonlinear effects according to a Wiener-Hammerstein structure with coefficients extracted from a Class AB amplifier introduced in [3]. This structure includes a memoryless nonlinear block surrounded by a leading linear filter, \( H_1(z) \), and lagging linear filter, \( H_2(z) \). These are given by

\[ H_1(z) = \frac{1 + 0.5z^{-2}}{1 - 0.2z^{-1}} \quad H_2(z) = \frac{1 - 0.1z^{-2}}{1 - 0.4z^{-1}} \]  

(13)

with memoryless nonlinear block coefficients

\[ a_1 = 1.0108 + 0.0858j \]
\[ a_3 = 0.0879 - 0.1583j \]
\[ a_5 = -1.0992 - 0.8891j \]  

(14)

The input signal is a baseband 3-carrier quadrature phase-shift keying (QPSK) signal with square-root raised cosine pulse-shaping and rolloff factor 0.22. A low level additive white Gaussian noise, SNR=78dB, was added to the input signal to form a realistic noise floor. We have assumed the input signal to be the same batch of data for each iteration, which exhibits nearly monotonic convergence as performance saturates. If each iteration is performed on a new batch of data, we still get similar convergence with the same asymptotic levels with minor batch-to-batch fluctuations. The results are based on 32,000 data samples in each batch. All of the predistorters incorporated odd order nonlinearities up to the 5th order \( (K = 5) \) and had 10 filter taps \( (Q = 9) \) unless otherwise noted.

A. Monostatic & bistatic remote predistortion architecture results

Power spectral density results for monostatic (c) and bistatic (d) remote predistortion are plotted in Fig. 10. The spectrum resulting from the standard non-remote indirect learning based predistortion (b) is also plotted for comparison. Trace (a) shows the uncompensated PA output and (f) the original input. The results show that the monostatic and bistatic remote predistortion approaches are able to achieve equal suppression of out-of-band intermodulation products. Additionally, these remote versions of predistortion are both able to match the performance of the standard non-remote predistortion, showing efforts to overcome the lack of signal access and delay matching complications of remote predistortion were effective.

![Fig. 10. Effectiveness of monostatic and bistatic remote predistortion at suppressing intermodulation. (a) PA output without compensation, (b) PA output using standard indirect learning predistortion, (c) PA output using monostatic remote predistortion (overlaps), (d) PA output using bistatic remote predistortion (overlaps), (e) Output from predistorter (uplink), (f) Original input.](image)

The equivalent performance of these predistortion techniques can also be seen according to three related measures of distortion shown in Table 1. These measures are defined as the following:

- **Adjacent channel power** (ACP) measures the ratio of power (due to distortion introduced by intermodulation) in a directly adjacent channel of equivalent bandwidth to the amount of power in a single carrier channel. Due to the channel roll-off and noise floor, the input signal had an ACP of -71.5 dB. This limits the achievable ACP of any of the simulated predistortion techniques.

- **Error-vector magnitude** (EVM) is a measure of in-band signal distortion. Specifically, it measures the power of the demodulated constellation error between the input and PA output normalized to the

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power of the constellation. Due to residual inter-symbol interference (ISI) inherent to pulse-shaping, the input signal had an EVM of -47.1 dB. This limits the achievable EVM of any of the simulated predistortion techniques.

- The signal-to-distortion ratio (SDR), the ratio of signal power to error power, is measured between the input to the predistorter and the PA output.

<table>
<thead>
<tr>
<th>Predistortion</th>
<th>ACP (dB)</th>
<th>EVM (dB)</th>
<th>SDR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard ILA</td>
<td>-69.8</td>
<td>-47.1</td>
<td>67.9</td>
</tr>
<tr>
<td>Monostatic</td>
<td>-69.7</td>
<td>-47.1</td>
<td>68.8</td>
</tr>
<tr>
<td>Bistatic</td>
<td>-69.6</td>
<td>-47.1</td>
<td>67.5</td>
</tr>
</tbody>
</table>

**TABLE I**
Comparison of performance measures between the standard indirect learning architecture with the remote monostatic and bistatic versions of indirect learning

Each remote and non-remote predistortion technique achieved a ACP of approximately -70 dB, an EVM of approximately -47 dB, and SDR of approximately -68 dB. Both the ACP and EVM results closely match that of the input signal as desired. Performance here does not incorporate the effects of AWGN and restrictions on uplink out-of-band power which our simulation efforts turn to next.

### B. Noise reduction results

AWGN was introduced on the uplink and downlink with simulated values of $E_b/N_0=65$ dB on the uplink and $E_b/N_0=35$ dB on the downlink. Power spectral results for the noise reduction technique are plotted in Fig. 11. Using the noise reduction technique (c), the intermodulation power was reduced over the case where it was not applied (b). While the downlink AWGN was applied to the signal in training, it does not appear in the results since it enters after the PA output.

Although the ACP measure does not capture the full extent of out-of-band improvement, results are included in Table 2. Adjacent channel power was reduced by only 3 dB, but we can see from the plot that much of the intermodulation power occurred just out side the bounds of the adjacent channel power measure. Perhaps more notable, the SDR and EVM both increased significantly. Thus, significant residual distortion caused by the AWGN also occurred in-band and but the improvement cannot be observed in Fig. 11.

**TABLE II**
Comparison of remote predistortion performance measures with and without the noise reduction technique applied

<table>
<thead>
<tr>
<th>Noise reduction</th>
<th>ACP (dB)</th>
<th>EVM (dB)</th>
<th>SDR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not applied</td>
<td>-60.7</td>
<td>-38.7</td>
<td>37.5</td>
</tr>
<tr>
<td>Applied</td>
<td>-63.4</td>
<td>-47.0</td>
<td>57.1</td>
</tr>
</tbody>
</table>

**C. Reducing uplink adjacent channel intermodulation results**

A low-pass FIR filter with pass-band to stop-band ratio of 1:0.18 was used in the prefiltering the inverse simulation. The predistorter was selected to have 3rd-order with memory 10. The nonlinear order was reduced here to help manage the amount of out-of-band correction applied by the predistorter. Spectral results for this technique are plotted in Fig. 12.

The dual inverses technique was simulated using $\alpha=0.45$, which set the proportion of non-linear predistortion to the linear predistortion when combined into a single predistorted signal. The non-linear predistorter was selected to have 3rd-order with memory 10. Again, the reduction in nonlinear order assisted in managing the out-of-band correction applied by the predistorter. The power spectral results for this technique are plotted in Fig. 13.

In each technique, the adjustable parameter, i.e. pass-to-stop band ratio or $\alpha$, was selected such that the uplink intermodulation distortion was no greater than the intermodulation distortion of the uncompensated down-
Fig. 12. Effectiveness of pre-filtering the inverse at suppressing adjacent channel intermodulation in the uplink and downlink. (a) PA output without compensation, (b) Predistorted output (uplink), (c) PA output (downlink), (d) Original input.

Fig. 13. Effectiveness of the dual inverses technique at suppressing intermodulation in the uplink and downlink. (a) PA output without compensation, (b) Predistorted output (uplink), (c) PA output (downlink), (d) Original input.

link. Since this technique would be applied to satellites already in orbit, it is assumed that their downlink spectrum previously met regulatory limits. Here our uplink signal will be restricted to meet the same regulated levels of adjacent channel intermodulation while providing for some “head room” on the downlink.

Using both techniques, with the uplink intermodulation distortion constrained, the amount of adjacent channel intermodulation on the downlink signal was reduced as desired. From an uncompensated downlink ACP of -43.9 dB, the prefiltering the inverse technique reduced downlink ACP to -50.3 dB and the dual inverses technique reduced downlink ACP to -49.3 dB. Results are tabulated in Table 3.

<table>
<thead>
<tr>
<th>Uplink intermod. reduction technique</th>
<th>Adjacent channel power (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None applied</td>
<td>Uncomp.</td>
</tr>
<tr>
<td></td>
<td>Downlink</td>
</tr>
<tr>
<td>None applied</td>
<td>-43.9</td>
</tr>
<tr>
<td>Prefilter inverse</td>
<td>-43.9</td>
</tr>
<tr>
<td>Dual inverses</td>
<td>-43.9</td>
</tr>
</tbody>
</table>

TABLE III
COMPARISON OF REMOTE PREDISTORTION ADJACENT CHANNEL PERFORMANCE WITH THE PREFILTERING THE INVERSE AND DUAL INVERSES TECHNIQUE APPLIED, WHERE * INDICATES THE ACP LEVEL MAY NOT MEET REGULATORY SPECIFICATIONS

While these techniques focused on reducing out-of-band intermodulation, the in-band measures of EVM did not degrade significantly. Without any reduction technique applied, the EVM was -47.1 dB. The EVM was -46.8 dB and -44.8 dB in the prefiltering the inverse and dual inverses techniques respectively.

VII. CONCLUSIONS

Remote predistortion encounters four unique complications not faced in the standard indirect learning predistortion when applied to ground-based accessible PAs. Two remote predistortion approaches based on the indirect learning architecture were introduced in this study. The monostatic method was shown to be able to compensate for the long, time-varying satellite round-trip delay effectively. Demodulating and remodulating the signal when using the bistatic method was shown to effectively eliminate the signal access problem. By forward modeling the PA, we were able to remove the coefficient biasing effects when AWGN was introduced to the uplink and downlink signals. Finally, the balance between the uplink and downlink intermodulation power was managed using the two techniques proposed. Achieving their objective, they both reduce the downlink intermodulation power when compared to the uncompensated downlink while, at the same time, balancing the uplink and downlink intermodulation.

VIII. FUTURE RESEARCH

Many refer to the predistortion technique studied here as waveform predistortion since predistortion is applied to a highly upsampled waveform. A related technique known as data predistortion applies predistortion to the signal constellation, i.e. a signal before it is upsampled and pulse-shaped. The data predistortion technique does
not attempt to compensate for the out-of-band intermodulation distortion, rather it relies more heavily on the output filtering of the PA (not relied upon in this study) to remove these effects. This technique instead focuses on compensating for in-band constellation distortion. The overall effectiveness of this form of predistortion will be studied in more depth in future research.

IX. BIBLIOGRAPHY


