

Self-Interference Cancellation in In-band Full Duplex Systems (IBFD) Using Radial Basis Function Neural Networks (RBFNN)

Khaled M Gharaibeh¹

^{1,3}Department of Telecommunication Engineering, Yarmouk University, Jordan

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ABSTRACT

In-band Full Duplex (IBFD) wireless systems have attracted attention for use in emerging wireless systems as they provide significant enhancement to system capacity over traditional techniques. In IBFD, transmission and reception occur simultaneously and on the same frequency band. Thus, the main challenge in system design is self-interference (SI) where the strong transmit signal leaking to the receiver interferes with the weak received signal. SI typically includes a nonlinear component resulting from the transmitter Power Amplifier (PA); therefore, the resulting SI is highly dependent on transmit power. In this paper, an SI cancellation (SIC) scheme for IBFD systems is presented and verified. The proposed nonlinear SIC scheme is based on using a Radial Basis Function Neural Network (RBFNN) to model the nonlinear SI. A practically motivated feature representation which includes instantaneous power of the transmit signal is introduced, enabling efficient modelling of amplitude-dependent and memory-dependent nonlinearities. The proposed RBFNN canceller offers localized approximation capability and inherently stable training structure, making it suitable for addressing the SI dependence on transmit power. Simulation results demonstrate that the RBFNN-based SI canceller outperforms model-based cancellers such as the Memory Polynomial (MP) cancellers by 10 dB across a transmit power range of 30 dB.

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Corresponding Author:

Khaled M Gharaibeh,
Department of Telecommunication Engineering,
Yarmouk University,
Irbid, Jordan.
Email: kmgharai@yu.edu.jo

1. INTRODUCTION

Traditional capacity enhancement technologies such as advances in modulation, coding and multiple antennas have reached their limits. In-Band Full Duplex (IBFD) technology, which has been employed in radar and repeater systems for a long time, has recently received significant attention as a non-traditional alternative for enhancing system capacity in emerging 6G systems. In an IBFD system, transmission and reception occur simultaneously over the same frequency band; therefore, the system can offer double the spectral efficiency of frequency division duplexing (FDD) systems [1]. The main challenge in IBFD systems is that simultaneous transmission/reception requires perfect isolation between the transmitter and receiver. Since perfect isolation is not realizable, the limited isolation of duplexers/circulators results in an inevitable level of self-interference (SI) as shown in Fig 1 [2], [3]. In 6G systems, small cells are used, hence, the SI problem becomes manageable as the received signal level is strong compared to systems that use large cells [4][5].

As shown in Figure 1, SI consists of a strong signal that leaks from the transmitter after it passes through the coupling channel as well as the receiver hardware. The leaked signal undergoes linear and nonlinear transformations before it is processed by the receiver as SI. Linear transformations include circulator leakage, antenna coupling, and other internal coupling mechanisms. Nonlinear transformations arise from transmitter power amplifier (PA) nonlinearity, digital-to-analog converter (DAC), analog-to-digital converter (ADC), IQ

imbalance and phase-noise [4]. The main two challenges in mitigating SI are the operating point changes and the time-varying nature of SI. These changes result from the magnitude and phase changes due to changes in the temperature, the operating frequency band or the dynamic multipath environment surrounding the wireless node.

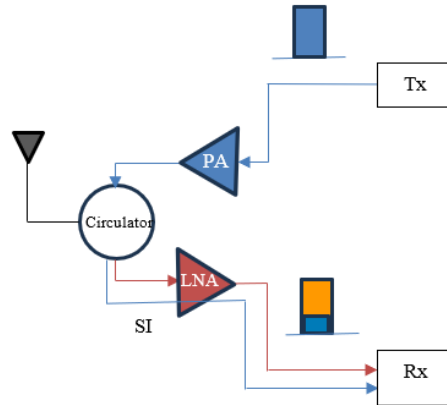


Figure 1. SI in IBFD systems.

To mitigate SI, several approaches have been used through development of cancellation schemes. The aim of SI cancellation (SIC) is to reduce SI to the noise floor of the receiver typically with suppression levels above 100 dB. The most basic SIC scheme is the passive suppression where the leaked signal from the transmitter is attenuated to prevent receiver saturation. However, passive suppression does not account for the linear and nonlinear time-varying transformations that exist in the path from the transmitter to the receiver [6]. In order to account for these transformations, analog RF cancellation has been used [4]-[10]. To account for linear time variations of SI, analog linear SIC schemes have been. However, perfect cancellation of SI in the analog domain is difficult when the SI channel is time-varying and/or exhibit a nonlinear behaviour, resulting in residual interference after analog cancellation.

Digital SIC has been proven to provide low cost and effective cancellation of both linear and nonlinear SI components. Digital SIC structures are typically based on nonlinear models where the model parameters are extracted by training the SIC structure with real data [11], [12]. The most common models used in digital SIC schemes are the polynomial-based models such as Memory Polynomials (MP's) and the Volterra-type models such as the Wiener and Hammerstein structures [7]. The main limitation of polynomial based digital SIC schemes is their fixed global nature which limit their ability to model time-varying SI behaviour [12]. Although this can be overcome by using adaptive structures where the model is retuned frequently, this retuning is usually time consuming and degradation of performance. Furthermore, MP models are typically more suited for soft nonlinearities as their computational complexity grows rapidly with increasing the nonlinear order and memory depth [11].

In contrast to structured polynomial-based models, Neural Network (NN) models do not require prior knowledge of the nonlinear distortion model as they learn the nonlinear mapping directly from data [1][4]. NN models learn the nonlinear mapping directly from data. Therefore, they have been employed in digital SIC schemes and adaptive canceller tuning. For example, Feedforward NN's (FFNN's) have been used in memoryless nonlinear SIC architectures [13]. For SI with memory effects, Recurrent NN (RNN) architectures such as long short-term memory (LSTM) and gated recurrent unit (GRU) networks have been introduced [8]-[19]. NN models have also been used in adaptive SIC schemes which account for time-varying conditions of the SI channel. In this context, NN have been shown to enhance the convergence speed of the adaptive structure [9].

The main challenge of using NN-based in the design of SIC schemes is their high computational complexity. For example, Deep recurrent and convolutional architectures depend on iterative gradient-based optimization which leads to high computational complexity [8]. On the other hand, NN based SIC schemes which rely on global representations, require frequent retraining when SI is dependent on transmit power, e.g. PA induced SI. This frequent retraining results in increased computational complexity and renders the SIC structure impractical [3].

In this work, the use of radial basis function neural networks (RBFNN) for cancellation of nonlinear SI in IBFD systems is investigated. This is motivated by localized behaviour of RBFNN's making it well suited for cancellation of power dependent SI. Furthermore, the parameter extraction process of the RBFNN model can be done through ridge regression, resulting in more computationally efficient training than other NN models.

The proposed digital cancellation scheme utilizes RBFNN for modelling PA induced SI with finite memory is proposed and verified. The proposed scheme uses a two-stage architecture where the first stage is a linear canceller that suppresses the effects of the time-varying linear coupling channel, while the second stage suppresses nonlinear residual SI [3]. The proposed scheme is evaluated through a simulated SI scenario in an IBFD system. The performance of the proposed scheme is evaluated at different transmit power levels and compared to conventional linear and polynomial-based nonlinear cancellers. The simulation results show that the proposed canceller offers improved cancellation of SI and robustness against transmit power changes.

The main contributions of this paper are summarized as follows:

1. An RBFNN-based SIC scheme for IBFD systems is proposed and verified. The model accounts for operating-point variations and memory effects of the nonlinear elements in the transmit-receive path. The RBFNN consists of a single hidden layer and is linear in parameters enabling efficient and stable training via closed form solution.

2. The model uses a feature vector that includes instantaneous power which enables amplitude-dependent nonlinearities of the PA to be captured.

3. The proposed model is evaluated via simulated IBFD system which includes a linear coupling channel and a nonlinearity with memory. The input signals are constructed using 5G specifications and is used for training the RBFNN model. The performance of the SIC scheme assessed by evaluating the cancellation depth and is shown to achieve up to 10 dB improvement compared to MP cancellers over a wide range of transmit power.

The remainder of the paper is organized as follows: Section 2 presents the formulation of SI problem in IBFD system, Section 3 presents the proposed RBFNN-based cancellation framework, Section 4 presents the simulation setup and evaluation of performance, and Section 5 is a conclusion.

2. SELF-INTERFERENCE IN IBFD SYSTEMS

As shown in Figure 1, the simultaneous transmission and reception over the same frequency band in IBFD systems results in a portion of transmitted signal to leak to the receiver causing SI. This leaking of the transmit signal is due to the limited isolation of the duplexers which provide different paths for both signals. Figure 2 illustrates an IBFD SI cancellation system where the SI signal $i_{SI}(n)$ is superimposed on the desired received signal $s(n)$ and an AWGN signal $w(n)$. Therefore, the signal present at the receiver after Analog to Digital (A/D) conversion, can be written as [1]:

$$y(n) = s(n) + i_{SI}(n) + w(n) \quad (1)$$

The SI signal is basically the transmitted signal $x(n)$ after being processed by the nonlinear PA and by the linear coupling channel. The output of the PA can be written as [20]**Error! Reference source not found.**:

$$z(n) = f_{PA}(x(n)) \quad (2)$$

where $f_{PA}(\cdot)$ is a nonlinear transformation that includes memory effects. The output of the PA is then transformed by the linear coupling channel which represents the physical path between the transmitter and the receiver. The linear coupling channel is modeled by an impulse response $h_{SI}(n)$. Therefore, the SI signal can be written as [3]**Error! Reference source not found.**:

$$i_{SI}(n) = \sum_{k=0}^{L-1} h_{SI}(k)z(n-k) \quad (3)$$

where L is the memory depth of the linear channel. This impulse response models the coupling channel as a multipath channel which consists of a dominant leakage path and several weaker multipath reflections with random phases. An exponential decay can be included to emulate physical attenuation and overall isolation along the main path.

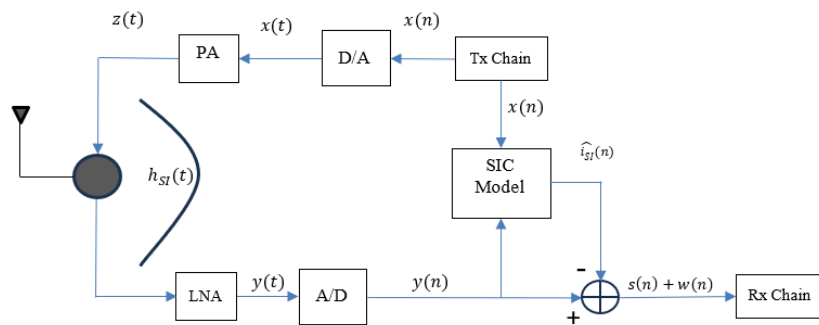


Figure 2. SIC in IBFD system

As shown in Fig 2, SI cancellation is achieved by subtracting an estimate of the transmitted signal from the total received signal $y(n)$. The goal of SIC is to construct an estimate $\hat{i}_{SI}(n)$ from the transmitted signal $x(n)$ and then subtract it from the received signal such that [11][12]:

$$e(n) = y(n) - \hat{i}_{SI}(n) \quad (4)$$

which ideally yields $s(n) + w(n)$ (i.e., SI suppressed below the noise floor).

Since the transmitted signal undergoes a cascade of nonlinear and then linear transformations, the SI signal in (3) can be written as [7]

$$i_{SI}(n) = i_{SI}^{lin}(n) + i_{SI}^{nl}(n) \quad (5)$$

where $i_{SI}^{lin}(n)$ represents the linear SI component that arises from the linear coupling of the transmitted signal to the receiver; and $i_{SI}^{nl}(n)$ represents the nonlinear component which results from processing the transmit signal by the PA nonlinearity. Note that this model assumes a perfect synchronization between the local oscillators at the transmitter and receiver, hence, phase noise and IQ imbalance contributions to the SI are ignored. These factors can be easily embedded in the linear and nonlinear components of (5) but we will ignore them for the moment since the focus of the paper is on modelling and cancellation of power dependent PA induced nonlinear SI.

Based on (5), the cancellation process can be done in two stages. The first suppresses the linear part of $i_{SI}(n)$ by a linear canceller, while the second, cancels the residual nonlinear SI $i_{SI}^{nl}(n)$ as will be seen in the following subsections.

2.1 Linear SIC

The linear component in (5) can be cancelled using standard linear cancellation where an estimate $\hat{i}_{SI}^{lin}(n)$ is constructed for the linear component of SI while the nonlinear component ($i_{SI}^{nl}(n)$) is considered as noise as shown in Figure 3. Assuming that the received signal $s(t)$ in (1) is not present during the estimation period, the residual signal in (4) can be written as [3][20]:

$$e(n) = y(n) - \hat{i}_{SI}^{lin}(n) = i_{SI}^{nl}(n) + w(n) \quad (6)$$

The linear component of SI results from the path from Tx to Rx which can be modelled as a linear time-dispersive channel as [7]: **Error! Reference source not found.**

$$i_{SI}^{lin}(n) = \sum_{k=0}^{L-1} h(k)x(n-k) \quad (7)$$

where $h(n)$ represents the impulse of the linear coupling channel which can be estimated using linear estimation. Using (7), the received signal in (1) becomes:

$$y(n) = \sum_{k=0}^{L-1} h(k)x(n-k) + i_{SI}^{nl}(n) + w(n) \quad (8)$$

Let $\hat{h}(n)$ denote the estimate of the impulse response $h(n)$, then the estimate of the linear SI component is given by

$$\hat{i}_{SI}^{lin}(n) = \sum \hat{h}(k)x(n-k) \quad (9)$$

and the residual error after linear cancellation is:

$$e(n) = y(n) - \hat{i}_{SI}^{lin}(n) \quad (10)$$

Hence, the estimate of $h(n)$ can be developed by minimizing the residual error as:

$$\hat{h}(n) = \arg \min_h \sum_n |y(n) - \sum_k h(k)x(n-k)|^2 \quad (11)$$

This problem is often solved by Least Squares (LS), Least Mean Squares (LMS) or Recursive Least Squares (RLS) methods. Once the linear impulse response of the linear coupling is estimated, the linear part of SI can be cancelled using (6).

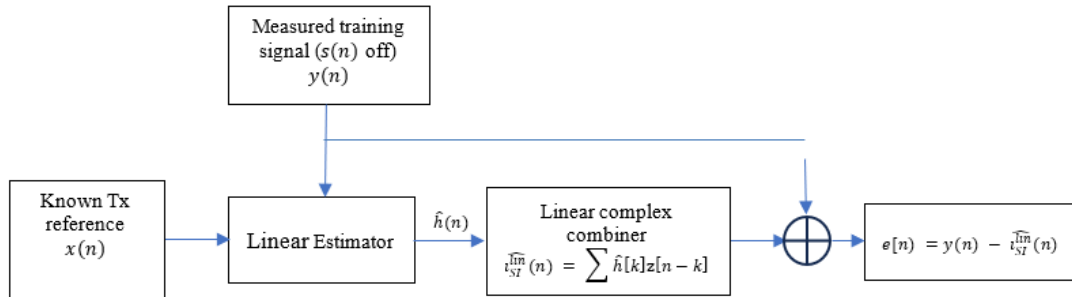


Figure 3. Parameter estimation of the linear SIC.

2.2 Nonlinear SIC

After linear cancellation, the residual SI is dominated by nonlinear distortion mainly induced by PA nonlinearity. The presence of nonlinear SI motivates the use of a nonlinear canceller in the second stage. In this stage, the nonlinear SI component $i_{SI}^{nl}(n)$ is estimated and subtracted from the residual signal $e(n)$ as shown in Fig 4.

To develop the nonlinear canceller, the nonlinear transformation that generates SI needs to be estimated. Let the nonlinear transformation be modelled as $z(n) = f(x(n), x(n-1), \dots, x(n-M))$ with a parameter vector $\mathbf{w}$, then the estimate of the nonlinear SI component $i_{SI}^{nl}(n)$ can be obtained by minimizing the residual as [7]

$$e_1(n) = e(n) - \widehat{i}_{SI}^{nl}(n) = s(n) + w(n) \quad (12)$$

The estimate of the parameter vector $\mathbf{w}$ can be obtained by minimizing the residual error $e_1(n)$ as:

$$\widehat{\mathbf{w}} = \arg \min_h \sum_n |e(n) - f[x(n), x(n-1), \dots, x(n-M)]|^2 \quad (13)$$

For example, if the nonlinear transformation f is modeled by a memory polynomial the [23]n:

$$i_{SI}^{nl}(n) = \sum_{p \in P} \sum_{m=0}^{M_p-1} a_{pm} x(n-m) |x(n-m)|^{p-1} \quad (14)$$

where P denotes the set of nonlinear orders and M_p is the memory depth for each order. The model parameters $\mathbf{w} = [a_{pm}]$ can be estimated using (13) as

$$\widehat{\mathbf{w}} = \arg \min_a \sum_n \left| e(n) - \sum_{p \in P} \sum_{m=0}^{M_p-1} a_{pm} x(n-m) |x(n-m)|^{p-1} \right|^2 \quad (15)$$

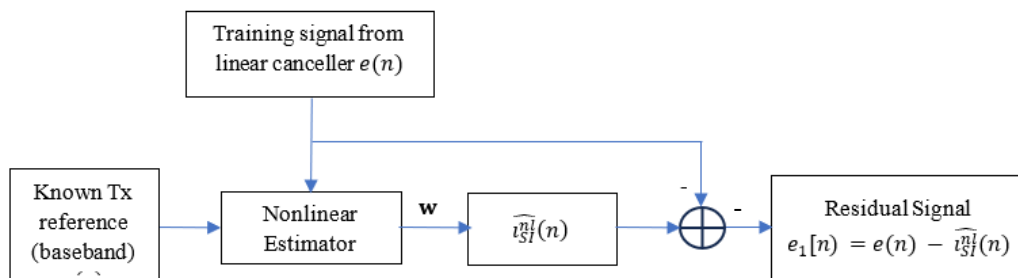


Figure 4. Block diagram of the RBFNN Nonlinear SIC.

The main limitation of the polynomial-based models is that their performance degrades as the nonlinearity becomes stronger. With strong nonlinearities, high order polynomials are needed to achieve acceptable approximation accuracy, but this leads to degradation of the model numerical stability. This motivates the use of more flexible models, such as neural networks, for nonlinear SI cancellation, which is addressed in the next section.

3. THE PROPOSED RBFNN SIC MODEL

As discussed in the previous section, after linear cancellation, the residual nonlinear SI from the output of the linear canceller is removed by estimating the nonlinear transformation $f(\cdot)$. In this section, an RBFNN model is used in the cascade structure to estimate the nonlinear SI from the output of the linear canceller according to Figure 5. The use of the RBFNN model is motivated by its localized behaviour making it suited for modelling operating point dependent nonlinearities as well as their memory effects.

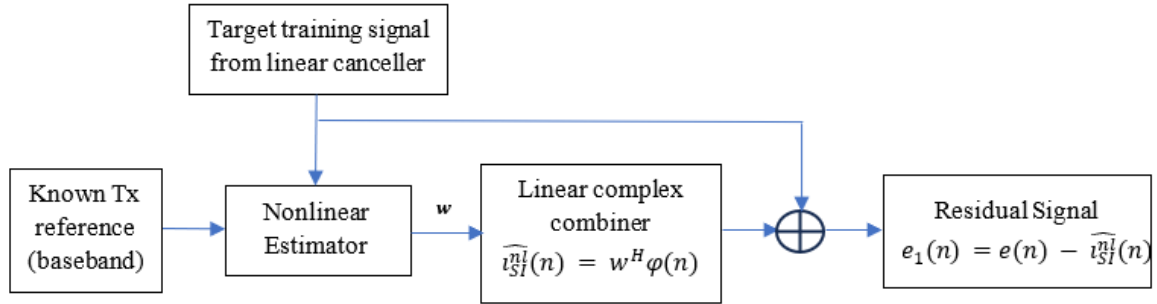


Figure 5. Training and operation of the RBFNN-based nonlinear SIC stage.

As shown in Figure. 5. The RBFNN model estimates the nonlinear SI component using the transmit reference signal, while cancellation is applied to the residual signal after linear SIC. The RBFNN nonlinear estimator is shown in Figure 6. The model consists of an input layer, a hidden layer and an output layer [21][22]. To develop the model, the network is fed with current and past transmit signal samples of a complex transmit reference signal $x(n)$ after normalizing its average power. Therefore, the input to the model is:

$$\bar{x}(n) = \frac{x(n)}{\text{rms}(x(n))} \quad (16)$$

The objective of normalizing the transmit signal prior to feature extraction is to improve numerical stability and robustness of the model across different power levels. To account for variations of the PA operating point as well as its memory effects, the feature vector at the output of the feature extraction block needs to include the in-phase and quadrature components of the transmit signal as well as its instantaneous power (represented by $|\bar{x}(n)|^2$), across multiple memory taps. Therefore, the feature vector is given by:

$$\mathbf{u}(n) = [\Re\{\bar{x}(n)\}, \Im\{\bar{x}(n)\}, |\bar{x}(n)|^2, \Re\{\bar{x}(n-1)\}, \Im\{\bar{x}(n-1)\}, |\bar{x}(n-1)|^2, \dots, \Re\{\bar{x}(n-M+1)\}, \Im\{\bar{x}(n-M+1)\}, |\bar{x}(n-M+1)|^2] \in \mathbb{R}^{3M} \quad (17)$$

where M is the memory depth of the model.

The hidden layer consists of L Gaussian radial basis functions (RBF) defined as [21]

$$\phi_l(\mathbf{u}(n)) = \exp\left(-\frac{\|\mathbf{u}(n) - \mathbf{c}_l\|^2}{2\sigma_l^2}\right), \quad l = 1, \dots, L \quad (18)$$

where: $(\mathbf{c}_l \in \mathbb{R}^{3M})$ is the l -th center, $(\sigma_l > 0)$ is the spread of the RBF. The Gaussian RBF is known for its desirable smoothness and numerical stability and provides localized nonlinear mapping as discussed in [12]. These unique properties make the RBFNN suitable for modelling nonlinear SI.

The RBF activation vector can be given by:

$$\boldsymbol{\phi}(n) = [\phi_1(\mathbf{u}(n)) \dots \phi_L(\mathbf{u}(n))]^T \in \mathbb{R}^L \quad (19)$$

For a network with a single hidden layer, the output layer produces the nonlinear component of the SI which is given as a weighted sum of the number of basis functions in the hidden layer as [21] **Error! Reference source not found.**:

$$\widehat{i}_{SI}^l(n) = \mathbf{w}^H \boldsymbol{\phi}(n) + b \quad (20)$$

where $\mathbf{w}$ is the NN complex weight vector, $(\cdot)^H$ indicates the Hermitian transpose and b is complex bias.

Note that the model constitutes a memory nonlinear model because $(\boldsymbol{\phi}(n))$ depends on the tapped-delay vector $(\mathbf{u}(n))$. Note also that although the RBF activations are real-valued, the output weights are complex-valued since the target signal is complex. The complex valued weights enable the in-phase and quadrature components to be modelled using a shared nonlinear basis.

The NN weight vector can be obtained by training the network with measured data as shown in Figure 5. The design matrix of the NN model is developed by considering a training interval of N samples (with the desired signal absent) as:

$$\boldsymbol{\Phi} = \begin{bmatrix} \boldsymbol{\phi}(0)^T \\ \boldsymbol{\phi}(1)^T \\ \vdots \\ \boldsymbol{\phi}(N-1)^T \end{bmatrix} \in \mathbb{R}^{N \times L} \quad (21)$$

where N is the length of the input signal. The NN weights $\mathbf{w}$ can be estimated by minimizing the error between the output of the RBFNN and the error at the output of the linear canceller as shown in Figure 5. Therefore, the weights are obtained by solving:

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}} \|\mathbf{e} - \boldsymbol{\Phi} \mathbf{w}\|^2 \quad (22)$$

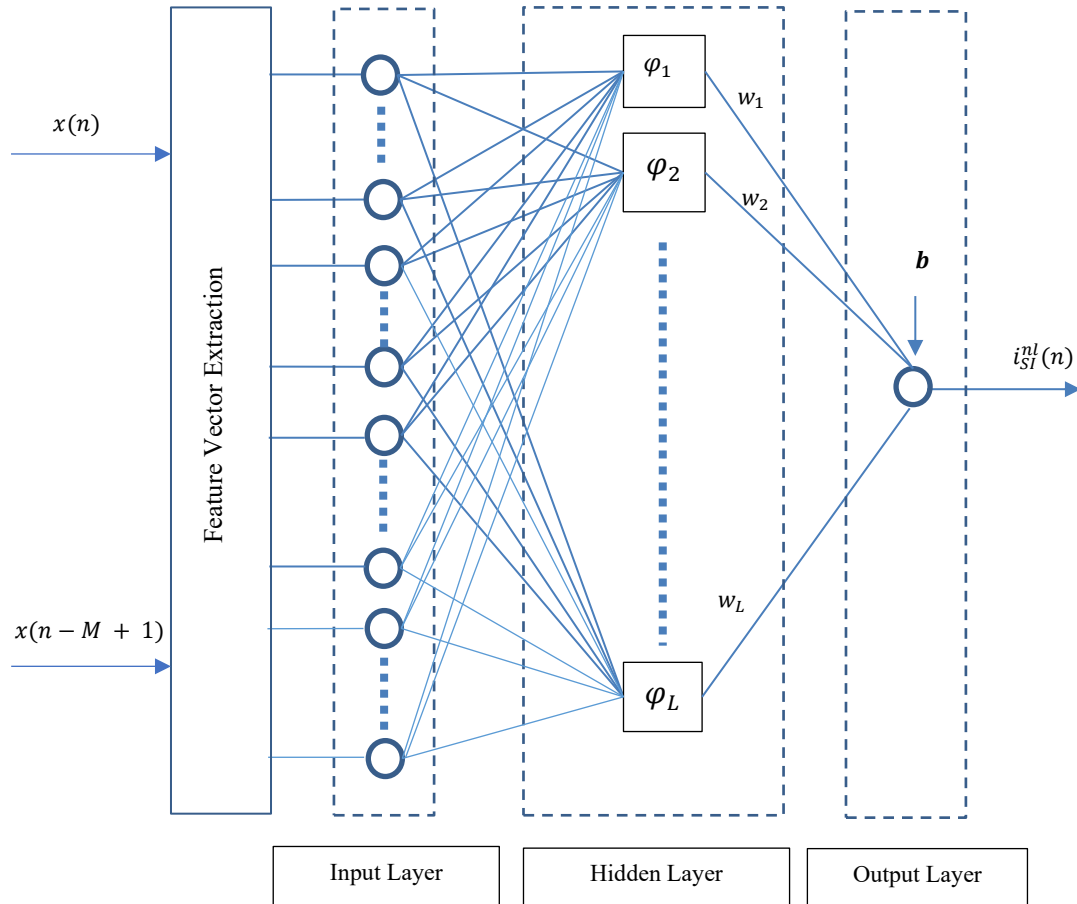


Figure 6. The internal structure of the RBFNN nonlinear SI estimator.

Assuming the received signal is absent, the target vector is defined as the error signal in (10) as

$$\mathbf{d} = \mathbf{e} = [e(0) \ e(1) \ \dots \ e(N-1)]^T \in \mathbb{C}^N \quad (23)$$

Thus, by using LS to solve (23), the NN weights are found as:

$$\hat{\mathbf{w}} = (\boldsymbol{\Phi}^T \boldsymbol{\Phi})^{-1} \boldsymbol{\Phi}^T \mathbf{d} \quad (24)$$

where transpose is used instead of the Hermitian transpose as the matrix Φ is real-valued. A regularized (ridge) version of the NN weight estimation problem is given by [21]:

$$\hat{\mathbf{w}} = (\Phi^T \Phi + \lambda \mathbf{I})^{-1} \Phi^T \mathbf{d} \quad (25)$$

where $\lambda > 0$ is a regularization parameter used to stabilize the LS solution.

The centers ($\mathbf{c}_l$) of the RBF can be computed by applying K -means approach to $\mathbf{u}(n)$ on training data. The spread σ_l can be selected globally based on average center distance. A common choice for finding the spreads σ_l is **Error! Reference source not found.**:

$$\sigma_l = \beta \cdot \frac{1}{K_l} \sum_{\mathbf{z} \in \mathcal{S}_l} \|\mathbf{u} - \mathbf{c}_l\|^2 \quad (26)$$

where ($\mathcal{S}_l$) is the set of samples assigned to cluster l , ($K_l = |\mathcal{S}_l|$), and β is a tuning constant (e.g., 1–2).

Once the NN is trained, the SI and the residual error at the output of the nonlinear canceller can be predicted as:

$$\widehat{i}_{SI}^{nl}(n) = \hat{\mathbf{w}}^H \phi(n) \quad (27)$$

$$e_1(n) = e(n) - \widehat{i}_{SI}^{nl}(n) \quad (28)$$

The attractiveness of the proposed model stems from the fact that training reduces to K -means clustering followed by LS estimation, which is fast and stable. The nonlinear canceller is linear in parameters which means that it can be trained efficiently using a single ridge-regression step. Consequently, the main advantage of the RBFNN model over other types of NN's is that its parameters (weights) can be obtained in closed form through ridge regression. This eliminates the need for iterative backpropagation, resulting in a computationally efficient training. Other similar low-complexity NN models such as shallow Multilayer Perceptron (MLP) and Extreme Learning Machines (ELMs) can be used. However, they rely on global nonlinear mappings as they employ global activation functions (e.g., sigmoid or ReLU).

Furthermore, unlike polynomial models which require a predefined structure, the RBFNN-based nonlinear model uses data-driven basis functions to adapt the representation of the nonlinearity. Although the evaluation of Gaussian RBFs can be more computationally demanding than evaluating polynomial models, hardware implementations can benefit from techniques such as fixed-point arithmetic, lookup-table (LUT) and polynomial approximation techniques, to avoid direct evaluation of exponential functions, thereby minimising the use of computing resources [32].

4. SIMULATION MODEL

The RBFNN SIC model is tested using simulation of the SI problem in MATLAB according to Fig 2. The RBFNN SIC is compared to a memory polynomial SIC with respect to cancellation depth. The following are the specifications of the major components of the simulation model.

4.1 Transmit Signal

The transmit signal is an OFDM signal generated according to the 5G standard. Table 1 shows the signal specifications.

Table 1. OFDM signal specifications

Sampling frequency (F_s)	15.36 MHz
Modulation	16 QAM
Subcarrier spacing	15 kHz
OFDM symbol time	66.67 μ s
FFT length	1024
Cyclic prefix length	72 samples
Number of OFDM symbols	600
BW	9 MHz

4.2 Linear Coupling Channel

The linear coupling channel in (7) is assumed to be a multipath channel which consists of a dominant leakage path and several weaker multipath reflections. The multipath components are assumed to have random phases (complex baseband) and amplitudes with mild exponential decay that emulate the physical attenuation and the overall isolation on the main path. These effects can be combined in an impulse response of the form [9][28]:

$$h_{SI}(n) = \alpha_0 e^{j\phi_0} \delta(n) + \sum_{i=1}^K \alpha_i e^{j\phi_i} \delta(n - d_i) e^{\beta k}, \quad n = 0, 1, \dots, L_h - 1 \quad (29)$$

where $\alpha_i = \alpha_0 \cdot 10^{20r_i}$, ϕ_0 and ϕ_i are the random phases of each reflection are uniformly distributed in $[0, 2\pi]$, $\alpha_0 = 10^{20C_{dB}}$ is the main path isolation, C_{dB} is the linear coupling depth, r_i and d_i are the gains and delays of the multipath channel, K is the number of multipath components, β is an exponential decay and L_h is the memory depth of the linear coupling channel. Table 2 provides the parameters of the impulse response of the linear coupling channel used in the simulations.

Table 2. Coupling channel parameters

d_i	[5 13 29]
r_i	[-15 -25 -32] dB
C_{dB}	-40 dB
K	3
L_h	64
β	-0.03

4.3 PA Nonlinearity

In order to examine the effectiveness of the RBFNN SIC, a PA nonlinearity with memory was generated. The PA model used here is intended to generate realistic nonlinear SI for evaluation purposes and is not intended as a high-fidelity behavioural PA model. The model is based on a Weiner Model which consists of a linear block followed by a memoryless nonlinearity and is realized as a discrete-time nonlinear dynamic system as shown in Figure 7 [20][24][26]. The output of the system is described in state-space form as

$$y(n) = f(s_s(n), s_f(n), v(n)) \quad (30)$$

where $f(\cdot)$ is a nonlinear transformation, $v(n)$ is an internal state variable which captures short-term electrical memory effects arising from bias networks and matching circuits and $s_f(n)$ and $s_s(n)$ are state variables which model fast and slow memory effects such as thermal dynamics and bias variation. As shown in Figure 7, the state variable $v(n)$ is modelled as a first-order linear IIR lowpass filter as [27]:

$$v(n) = (1 - \alpha_e)x(n) + \alpha_e v(n - 1) \quad (31)$$

where $x(n)$ is the complex baseband input signal, $\alpha_e = e^{\left(-\frac{1}{F_s \tau_{elec}}\right)}$ is the electrical memory coefficient, F_s is the sampling frequency and τ_{elec} is the electrical memory time constant (seconds).

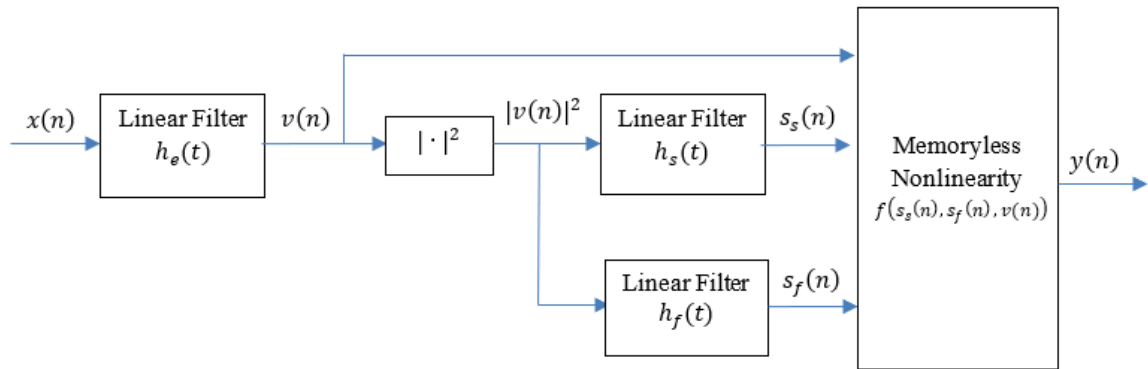


Figure 7. PA model with memory effects.

Inspired by electrothermal dynamics, where the junction temperature follows a first-order thermal system driven by dissipated power, the fast and slow memory effects are modelled state variables [29]:

$$s_f(n) = \alpha_f s_f(n - 1) + (1 - \alpha_f) |v(n)|^2 \quad (32)$$

$$s_s(n) = \alpha_s s_s(n - 1) + (1 - \alpha_s) |v(n)|^2 \quad (33)$$

where $|v(n)|^2$ is the instantaneous envelope power, and $\alpha_f = e^{-\frac{1}{F_s \tau_{fast}}}$, $\alpha_s = e^{-\frac{1}{F_s \tau_{slow}}}$ are the fast and slow memory coefficients and τ_{fast} and τ_{slow} are the fast and slow memory time constants respectively.

Now considering (30), the output of the model can be written as [30]:

$$y(n) = A_{out}(n) e^{j\phi(n)} \frac{v(n)}{|v(n)|} \quad (34)$$

where $A_{out}(n)$ and, $\phi(n)$ are memory-dependent nonlinear amplitude response phase rotation respectively. This representation separates amplitude and phase distortion and is commonly used in behavioural modelling of RF PA's [30]. The nonlinear amplitude response A_{out} is modelled using a smooth saturation function with state-dependent gain and saturation level, known as the Rapp model [30]:

$$A_{out}(n) = G_0 \frac{A(n)}{\left(1 + \left(\frac{A(n)}{A_{sat}}\right)^{2p}\right)^{\frac{1}{2p}}} \quad (35)$$

where $A(n) = |v(n)|$, p controls the smoothness of saturation, G_0 is a linear gain factor, A_{sat} is a saturation amplitude. The envelope slow and fast memory effects are incorporated in the amplitude $A_{out}(n)$ and the phase $\phi(n)$. This is achieved by replacing the linear gain G_0 by a memory-dependent gain factor $g(n)$ and replacing the constant saturation amplitude A_{sat} by a memory-dependent saturation amplitude $A_{sat,eff}(n)$:

$$A_{out}(n) = g(n) \frac{A(n)}{\left(1 + \left(\frac{A(n)}{A_{sat,eff}(n)}\right)^{2p}\right)^{\frac{1}{2p}}} \quad (36)$$

Table 3. PA model parameters.

Parameter	Value
F_s	15.36×10^6 Hz
τ_{elec}	$0.15 \mu s$
τ_{fat}	$0.3 \mu s$
τ_{slow}	$3 \mu s$
A_{sat}	1.2
p	3
$\beta_{g,f}$	0.15
$\beta_{g,s}$	0.25
β_A	0.15
α_{pm}	0.08
G_0	1

The memory-dependent gain factor and saturation amplitude can be defined in terms of slow and fast memory state variables as

$$g(n) = \frac{1}{1 + \beta_{g,f} s_f(n) + \beta_{g,s} s_s(n)} \quad (37)$$

and

$$A_{sat}(n) = \frac{A_{sat}}{1 + \beta_A s_s(n)} \quad (38)$$

where $\beta_{g,f}$ couples fast state to gain compression, $\beta_{g,s}$ couples slow state to gain compression and β_A is the saturation shift coefficient. Note that this reciprocal form provides a bounded and smooth approximation of dynamic gain compression due to memory effects.

Finally, the memory-dependent phase rotation in (34) can be defined in terms of the slow memory state variable as:

$$\phi(n) = \alpha_{pm} s_s(n) \quad (39)$$

where α_{pm} is a phase-memory sensitivity coefficient.

Table 2 shows the parameters used to generate the PA nonlinearity using the above model and Figure 8 illustrates the resulting nonlinear characteristics.

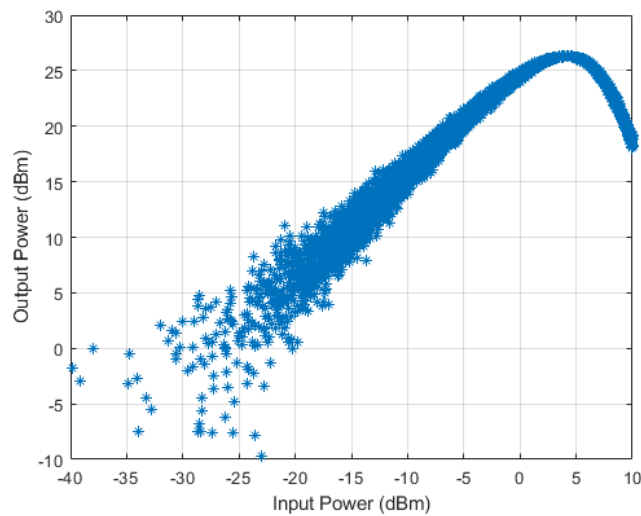


Figure 8. PA nonlinear characteristics (AM/AM) of the nonlinearity with memory effects.

4.4 RBFNN SIC

The RBFNN model used in the cancellation scheme was developed according to Fig 6. Table 4 lists the parameters used to develop the model. The number of neurons in the hidden layer was selected to evaluate the modelling accuracy. In practical implementations, this number can be reduced using techniques such as pruning, center merging or adaptive center selection resulting in much lower number of neurons and hence, computational complexity. Furthermore, the computational complexity that results from the K-means clustering does not practically add to the computational complexity of the model as this process can be performed during offline training.

Table 4. RBFNN model parameters.

Input memory depth	8
Number of RBF neurons (centers)	1100
Ridge regularization for output weights (λ)	10^{-5}
k-means iterations for center selection	25
Number of samples used to fit k-means centers (speed)	5000
SNR	40 dB

4.5 Performance Measures

The performance of the SI canceller is evaluated using the Cancellation depth (dB) which is defined as:

$$C_{dB} = 10 \log_{10} \left(\frac{E[i_{SI}^2]}{E[e^2]} \right) \quad (40)$$

The cancellation depth is typically evaluated when the desired received signal is off.

The cancellation gain of both MP and the RBFNN canceller over the linear canceller is computed as

$$C_{dB}^{gain} = C_{dB}^{nl} - C_{dB}^{lin} \quad (41)$$

5. RESULTS AND DISCUSSION

Figure 9 shows the power spectral density (PSD) of the transmit signal at an input power of -5 dBm which is close to the compression point of the PA. The transmit signal was used as a reference signal for the SIC scheme. Figure 10 shows the PSD of the signal after being processed by the linear coupling channel and the nonlinear PA. This signal is used as a training signal for both the MP and RBFNN cancellers and represents the SI signal. The figure demonstrates how the combined linear coupling channel and the nonlinear transformation distorts the in-band portion of the spectrum and result in out-of-band distortion.

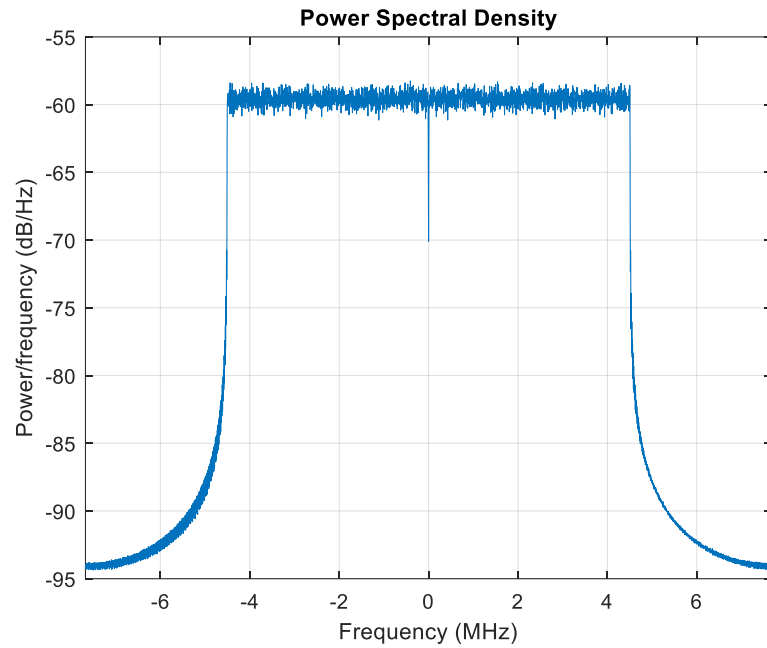


Figure 9. PSD of the transmit OFDM signal at input power of -5 dBm.

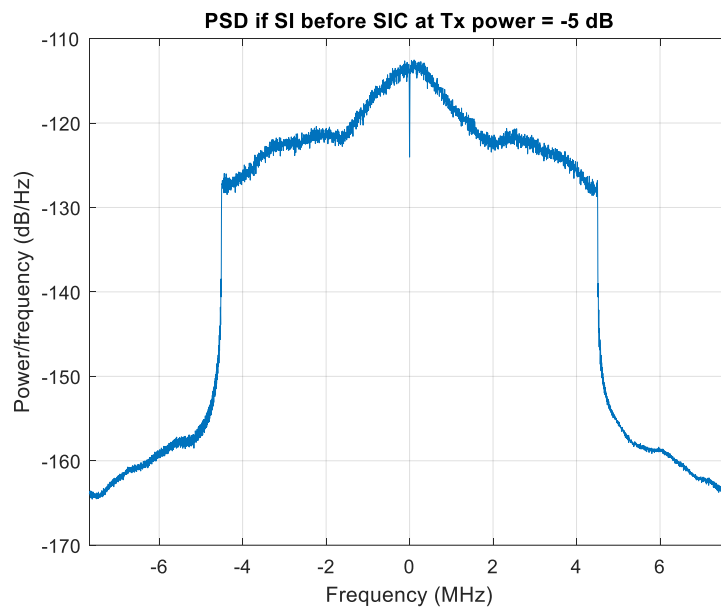


Figure 10. PSD of the SI signal at input power of -5 dBm.

The performance of the proposed RBFNN canceller was compared to the memory-polynomial-based canceller given in (14) with memory depth of $M_p = 8$ and an order of $P = 7$. Figure 11 shows the PSD of the residual signal after cancellation by a linear, MP and RBFNN cancellers at moderate transmit power (-5 dBm). The figure demonstrates that the proposed RBFNN canceller provides significantly higher cancellation than the MP and linear canceller alone. To assess the cancellation depth of the three cancellers at different transmit power levels, the cancellation depth was computed over swept transmit power in the range [-20, 10] dBm.

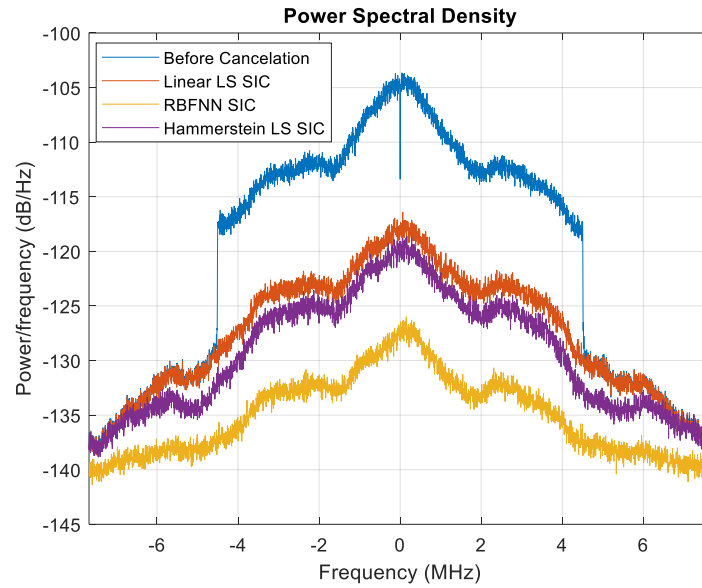


Figure 11. PSD of the residual signal after SIC with different models of the SI channel.

Figure 12 shows the cancellation depth of the three cancellers vs. transmit power. At low transmit power, the SI is predominantly linear. Consequently, the linear LS canceller achieves high cancellation performance, similar to the MP and the RBFNN cancellers whose nonlinear stages provide little cancellation gain due to the absence of nonlinear distortion. In this power range, the linear canceller provides a 40 dB cancellation which is equal to the used SNR indicating that the residual signal consists only of white noise. As the transmit power increases, the PA is driven deeper into its nonlinear region of operation. Consequently, the linear canceller cannot suppress the nonlinear SI component while the nonlinear cancellers begin to effectively mitigate it. The figure demonstrates that the RBFNN canceller outperforms both the linear and the MP canceller providing a 7 dB gain over the MP canceller and a 9 dB gain over the linear canceller when the PA is operated near compression (10 dBm).

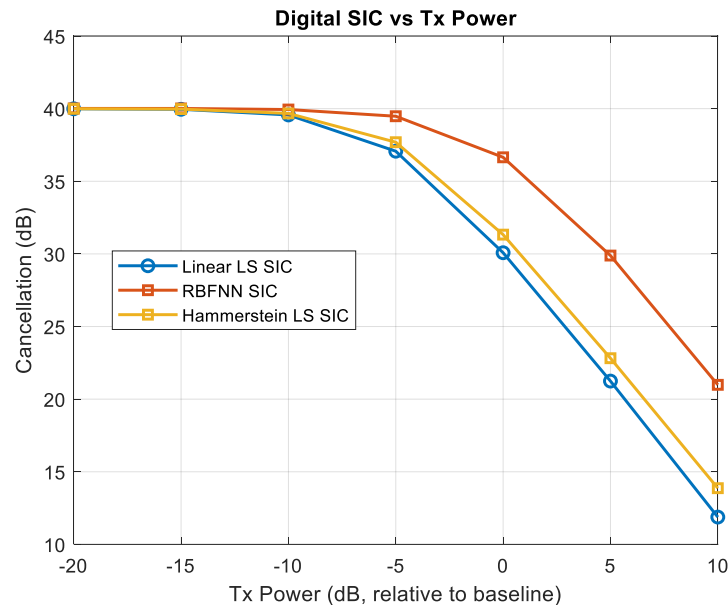


Figure 12. Cancellation depth for linear, MP and RBFNN cancellers.

Figure 13 demonstrates the superiority of the proposed canceller over MP canceller with regards to the cancellation gain defined in (41). This result indicates that the usable transmit power is extended by this cancellation gain resulting in improved performance of the IBFD system.

The above results demonstrate the improved performance of the RBFNN canceller over the polynomial-based cancellers. This can be attributed to the localized nature of the RBFNN model which enables the model to represent changes in transmit power more effectively than the global polynomial model.

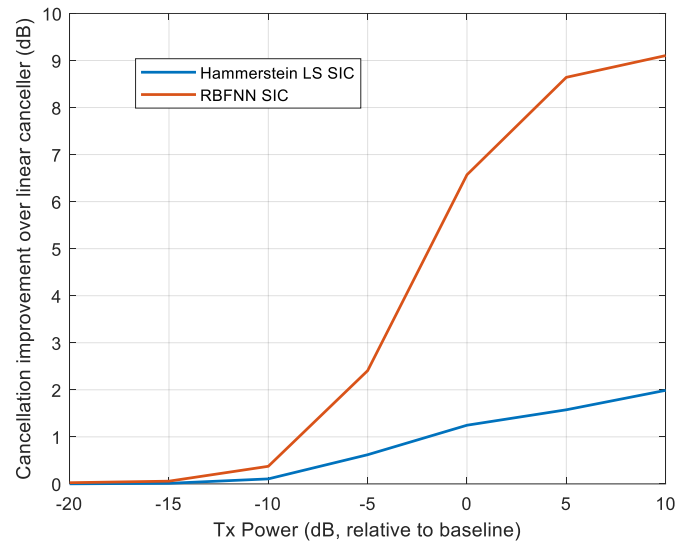


Figure 13. Cancellation gain over linear canceller for the MP and the proposed RBFNN canceller.

6. CONCLUSION

A nonlinear SIC scheme for IBFD transceivers based on RBFNN's has been proposed and verified. The proposed model accounts for operating point changes of the nonlinear elements between the transmitter and receiver that give rise to nonlinear SI as well as their memory effects. The proposed model is evaluated using realistic signals based on 5G specifications; and a synthesized nonlinearity with memory. The simulation results demonstrate that the RBFNN-based canceller achieves up to 10 dB improvement in SI cancellation performance compared to MP cancellers over a wide range of transmit power. The results demonstrate that the proposed model provides reduced sensitivity to operating point changes compared to MP-based cancellers.

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BIOGRAPHY OF AUTHORS



Khaled M Gharaibeh received his B.S. and M.S. in Electrical Engineering in 1995 and 1998 respectively, both from Jordan University of Science and Technology, Irbid, Jordan and his PhD in Electrical Engineering in 2004 from North Carolina State University, Raleigh, NC. He is a Senior member of the Institute of Electrical and Electronics Engineering (IEEE), Microwave Theory and Techniques Society (MTTS), Jordan Engineers Association and the honor society Eta Kappa Nu. His research interests are nonlinear system identification, behavioral modelling of nonlinear RF circuits, Passive intermodulation Cancellation and wireless communications.