

I/Q Imbalance Compensation Using a Nonlinear Modeling Approach

Haiying Cao, Ali Soltani Tehrani, Christian Fager, *Member, IEEE*,
Thomas Eriksson, and Herbert Zirath, *Senior Member, IEEE*

Abstract—In-phase/quadrature (I/Q) imbalance is one of the main sources of distortion in RF modulators. In this paper, a dual-input nonlinear model based on a real-valued Volterra series is proposed for compensation of the nonlinear frequency-dependent I/Q imbalance. First, different sources of distortion are identified from experimental measurements, then a dual-input nonlinear I/Q imbalance model is developed. Further, the inverse model is used for I/Q imbalance compensation. Finally, the performance of the I/Q imbalance compensator is evaluated with both simulations and experiments. In comparison with previously published results, the proposed I/Q imbalance compensator shows significantly improved performance. Thus, we prove that a complete nonlinear I/Q imbalance compensation can minimize the effects of the RF modulator in high-performance digital communication systems.

Index Terms—In-phase/quadrature (I/Q) imbalance, measurement system, modulators, nonlinearities, Volterra series.

I. INTRODUCTION

THE MODULATOR is one of the most critical parts in modern communication systems. Any nonlinearities of the analog hardware in the modulator can adversely impact the performance of the entire system [1]. In-phase/quadrature (I/Q) imbalance is one of the main impairments originating from the modulator. In practice, the gain and phase imbalances in the I and Q branches are due to the fact that quadrature carriers in the modulator do not have exactly the same amplitudes and 90° phase difference. Asymmetry problems between the I and Q branches can also contribute to the imbalance.

Various methods have been proposed to compensate for the I/Q imbalance at the receiver side. In [2] and [3], an approach for a blind estimation and compensation of I/Q imbalance was proposed, where the parameter estimation does not depend on the structure of the received signals and no training signals are needed. In [4], a known repetitive training sequence was used in an adaptive least squares (LS) algorithm to estimate

the I/Q imbalance parameters, which could take the carrier frequency offset into consideration. In [5]–[8], finite impulse response (FIR) filters were introduced to compensate for the I/Q imbalance. Further, in [8], the I/Q imbalance compensator was used at the transmitter in connection with a predistorter for linearization of the nonlinear power amplifier. From the measurement results in [8], the I/Q imbalance compensator employed in the digital predistortion system could significantly improve the linearity of the transmitter. In these approaches, however, only linear I/Q imbalance was considered.

Recently, the effects of nonlinear distortion in I/Q modulators have received considerable attention in the literature, e.g., [9], [10]. The focus of these studies were, however, only on static nonlinearities, and nonlinear imbalance between the I and Q branches was not considered.

In this paper, we will show that the nonlinear I/Q imbalance has an important effect on practical modulators. A dual-input nonlinear model based on a real-valued Volterra series is proposed to model the I/Q imbalance. With this approach, the nonlinear and linear I/Q imbalances are modeled together, and the inverse model is used as the pre-compensator at the transmitter. Measurements with a vector signal generator (VSG) are used to demonstrate the potential of the proposed compensation scheme.

This paper is organized as follows. In Section II, the conventional I/Q imbalance model is discussed and the proposed model and its structure are presented. In Section III, the I/Q imbalance compensator is discussed and the method for model extraction is further explained. In Section IV, the measurement system setup is described, and the simulation and experimental results are shown in a comparative way. Finally, conclusions are drawn in Section V.

II. I/Q IMBALANCE MODEL

In general, both frequency-independent and frequency-dependent components of the I/Q imbalance exist in RF modulators. The frequency-independent I/Q imbalance can be characterized by an amplitude and phase error mismatch, and can be compensated for using the Gram–Schmidt procedure [11]. Frequency-dependent I/Q imbalance, which is considered in this paper, mainly originates from the analog components in the I and Q branches of the modulator. A simplified modulator model containing the analog components is shown in Fig. 1. These components may also introduce some undesirable nonlinear distortion: static memoryless nonlinearities are introduced by the D/A converters as quantization noise and dynamic range clipping, and nonlinearities with memory are

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H. Cao, C. Fager, and H. Zirath are with the Department of Microtechnology and Nanoscience, Chalmers University of Technology, SE-412 96 Göteborg, Sweden (e-mail: haiying@chalmers.se; christian.fager@chalmers.se; herbert.zirath@chalmers.se).

A. Soltani Tehrani and T. Eriksson are with the Department of Signals and Systems, Chalmers University of Technology, SE-412 96 Göteborg, Sweden (e-mail: asoltani@chalmers.se; thomase@chalmers.se).

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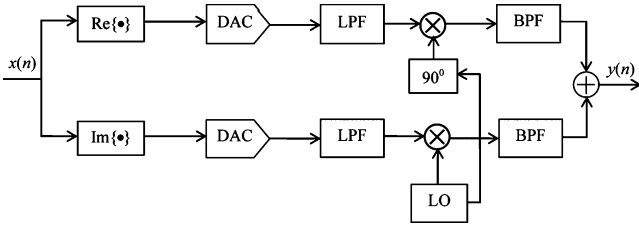


Fig. 1. Simplified model of I/Q modulator.

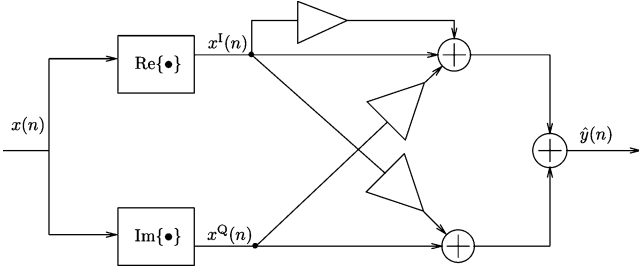


Fig. 2. Traditional I/Q imbalance model using gain components.

introduced by the analog low-pass reconstruction filter [9] and local oscillator (LO) phase offsets.

Traditionally, the I/Q imbalance is compensated for using cross-coupled gains to adjust the imbalance of the I and Q branches [12], as shown in Fig. 2. However, this kind of model is not sufficient to compensate nonlinear and/or frequency-dependent I/Q imbalance; more advanced schemes are required for this purpose.

In modeling general nonlinear systems with memory, the Volterra series is a very powerful tool [13]. Modified Volterra series are widely used for behavioral modeling of RF power amplifiers [14], [15]. It is important to realize, however, that the characteristic of power amplifiers—working around a fixed carrier frequency—does not depend on absolute phase shifts in the RF carrier. In consequence, the real (I) and imaginary (Q) parts are interchangeable from the amplifiers point of view. These facts are applied in the modified Volterra series used for power amplifier behavioral modeling, which, therefore, only have symmetric kernels [16]. Also, since the baseband version of the Volterra series just considers the frequency components of the signal that are around the carrier frequency, only odd-order nonlinear terms exist [17]. Such simplifying assumptions can not be used for I/Q modulator modeling; for full generality, an I/Q modulator model must include all nonlinear terms [9].

To compensate for the nonlinearities in the I and Q branches and the nonlinear frequency-dependent I/Q imbalance, a new application of the classical real-valued Volterra series is introduced in this paper.

The classical truncated real-valued Volterra series can be written as

$$y(n) = \sum_{m=0}^M h_m x(n-m) + \sum_{m_1=0}^M \sum_{m_2=m_1}^M h_{m_1 m_2} x(n-m_1) x(n-m_2)$$

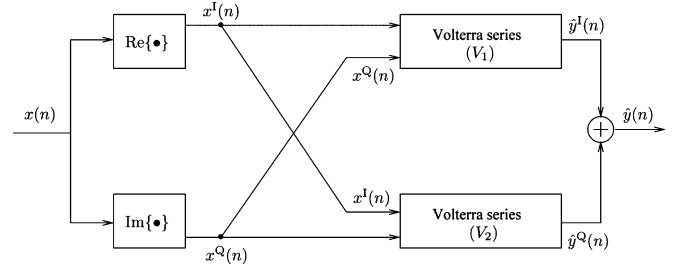


Fig. 3. Dual-input nonlinear I/Q imbalance model based on Volterra modeling.

$$+ \dots + \sum_{m_1=0}^M \dots \sum_{m_P=m_{P-1}}^M h_{m_1 \dots m_P} \cdot x(n-m_1) \dots x(n-m_P). \quad (1)$$

where $x(n)$ and $y(n)$ represent the input and output of the Volterra series, respectively. P is the nonlinear order, M is the memory depth, and h_{m_1, \dots, m_P} is the p th-order kernel of the Volterra series. Here, we extend the ordinary Volterra series (1) to a dual-input model using both the real and imaginary parts of $x(n)$ as the inputs to the model. Based on this, the complex output of the I/Q modulator will be modeled using two separate dual-input Volterra series with the real and imaginary parts of $y(n)$ as the output, respectively. To illustrate the principle of this I/Q imbalance model more clearly, a block diagram is shown in Fig. 3. Using this approach, (1) can be reformulated as

$$\hat{y}(n) = V_1[x^I(n), x^Q(n)] + jV_2[x^I(n), x^Q(n)] \quad (2)$$

where

$$V_i = \sum_{m_1=0}^M \mathbf{h}_{m_1}^T \mathbf{x}_{m_1} + \sum_{m_1=0}^M \sum_{m_2=m_1}^M \mathbf{h}_{m_1 m_2}^T (\mathbf{x}_{m_1} \otimes \mathbf{x}_{m_2}) + \dots + \sum_{m_1=0}^M \dots \sum_{m_P=m_{P-1}}^M \mathbf{h}_{m_1 \dots m_P}^T (\mathbf{x}_{m_1} \otimes \dots \otimes \mathbf{x}_{m_P}). \quad (3)$$

\otimes is used to denote the Kronecker product defined as

$$\begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \otimes \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} a_1 b_1 \\ a_1 b_2 \\ a_2 b_1 \\ a_2 b_2 \end{bmatrix} \quad (4)$$

vectors \mathbf{h} and \mathbf{x} are defined as

$$\mathbf{h}_{m_1 \dots m_P} = [h_{m_1 \dots m_P, 1}, h_{m_1 \dots m_P, 2}, \dots, h_{m_1 \dots m_P, 2^P}]^T \quad (5)$$

and

$$\mathbf{x}_{m_P} = \begin{bmatrix} x^I(n-m_P) \\ x^Q(n-m_P) \end{bmatrix}. \quad (6)$$

This model, which is based on dual-input real-valued Volterra series, not only includes the terms in each branch, but also the cross terms between I and Q branches. Consequently, it can be used to model both linear and nonlinear I/Q imbalances, as well as frequency-dependent I/Q imbalance.

III. I/Q IMBALANCE COMPENSATION

In Section II, a dual-input nonlinear model based on the real-valued Volterra series has been proposed to model both linear

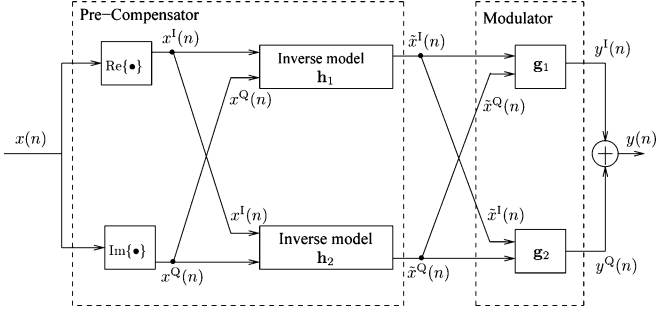


Fig. 4. Cascade of I/Q imbalance pre-compensator and modulator.

and nonlinear I/Q imbalances. Thus, the inverse model of this Volterra series can be constructed and used as the I/Q imbalance pre-compensator, as shown in Fig. 4, where \mathbf{h}_1 and \mathbf{h}_2 are the estimated kernels of the inverse Volterra model, and \mathbf{g}_1 and \mathbf{g}_2 denote the nonlinear functions in the modulator. Separate inverse models are used for the pre-compensators in the I and Q branches.

In order to find the kernels of the inverse models, identification has to be performed. Many methods have been proposed for the Volterra model identification [18], [19]. By definition, theoretically, the inverse model should produce the desired original signal as its output when fed with the modulator output signal as its input. Therefore, measurements of modulator output signal with a given input signal can be used for identifying the kernels of the inverse model.

As shown in (3), since the Volterra series is linear in terms of kernels, \mathbf{h} can be estimated by the least squares estimation (LSE) method. Assuming signal stationarity, a single global minimum is obtainable. With this method, the model error between the estimated signal and the original signal can be written as

$$\mathbf{e} = \mathbf{x} - \hat{\mathbf{x}} \quad (7)$$

and

$$\hat{\mathbf{x}} = \mathbf{Y}\mathbf{h} \quad (8)$$

where \mathbf{x} and $\hat{\mathbf{x}}$ denote the original and estimated signal vectors, respectively.¹ \mathbf{Y} is the modulator output signal matrix

$$\mathbf{Y} = [\mathbf{y}_{m_1}^T, (\mathbf{y}_{m_1} \otimes \mathbf{y}_{m_2})^T, \dots, (\mathbf{y}_{m_1} \otimes \mathbf{y}_{m_2} \otimes \dots \otimes \mathbf{y}_{m_p})^T] \quad (9)$$

where \mathbf{y}_{m_p} is defined similar as \mathbf{x}_{m_p} in (6). The size of \mathbf{Y} is $N \times J$, where N is the number of samples and J is the number of coefficients. The LSE solution to minimize the error variance can then be written as

$$\mathbf{h} = (\mathbf{Y}^T \mathbf{Y})^{-1} \mathbf{Y}^T \mathbf{x}. \quad (10)$$

In practice, the measurement noise associated with the output of the modulator will bias the solution slightly, and the nonlinear behavior of the modulator will change, depending on the

¹For simplicity, the superscripts indicating the real and imaginary parts of the signal have been omitted.

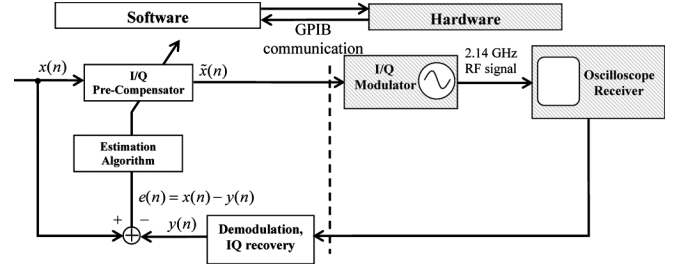


Fig. 5. Experimental setup used for evaluation of I/Q modulator pre-compensation methods.

temperature or variations of input signal power. In order to obtain good estimates of the kernels of the inverse model, adaptive training is needed [20].

IV. SIMULATION AND EXPERIMENTAL RESULTS

In this section, the performance of the proposed nonlinear I/Q imbalance pre-compensator in Section III is evaluated using a simple and flexible measurement system setup. The block diagram of this setup is shown in Fig. 5. The modulator used here is an Agilent E4438C VSG, and an Agilent 54845A digital storage oscilloscope (DSO) is used as a vector signal analyzer. The baseband I/Q signals are generated in software and then downloaded to the VSG. At the hardware level, the baseband I/Q signals are modulated to the RF signal. The DSO captures the RF signal and sends it back to the computer, where the RF signals are down-converted to baseband I/Q data. In order to decrease the noise variance and enhance the dynamic range of the signal, a statistical averaging technique is used [21]. In this paper, all experimental results are based on statistical averaging over 300 measurements. Each measurement involves a transmission of 20 000 samples of the input signal.

The input signal used in the experiments is an 8-MHz bandlimited white noise signal, which is modulated to a 2.14-GHz RF carrier at 3-dBm average power. Given this input signal, the I/Q imbalance pre-compensator is adaptively constructed based on the inverse model. The experimental procedure can be referred to Fig. 5, where $x(n)$ and $\tilde{x}(n)$ denote the original and pre-compensated I/Q data samples, respectively, and $y(n)$ is the down-converted received RF signal in complex baseband form.

The performance of the proposed I/Q imbalance pre-compensator is compared to the FIR filters in [22], the linear equalizer in [23], and the nonlinear equalizer in [9]. The result without any compensation scheme is also included as a reference. In order to evaluate the performance with different compensation techniques, the experimental results are shown for the following two cases.

Case A) *Artificially introduced I/Q offsets of 3% and 5%, respectively, and 3° I/Q skewness.* For this case, the assigned parameter values are typical of the ones observed in practical applications [24].

Case B) *No artificial I/Q imbalance.* For this case, the only distortion is due to imperfections in the VSG, which has very small I/Q imbalance.

TABLE I
COMPARISON BETWEEN DIFFERENT I/Q IMBALANCE COMPENSATION METHODS

Methods	Model Validation NMSE [dB]		Pre-compensation NMSE [dB]		Number of coefficients
	Case A	Case B	Case A	Case B	
Proposed dual-input nonlinear model with nonlinear order 3 and memory depth 4	-49.76	-50.48	-47.9	-49.39	285 × 2 (real)
Nonlinear equalizer in [9] with nonlinear order 3 and memory depth 4	-29.55	-49.68	-29.51	-47.17	205 (complex)
Linear FIR filters in [22] with 20 taps	-46.1	-46.42	-45.9	-45.67	20 × 2 (real)
Linear equalizer in [23] with 20 taps	-29.47	-46.11	-29.39	-45.42	20 (real)
No Compensation Scheme	Case A -29.26	Case B -43.18			

A. I/Q Imbalance Model Validation

Before the I/Q pre-compensator is used to pre-compensate the modulator input signal, the performance of the inverse model, which is used to construct the I/Q pre-compensator (see Fig. 4) is validated. This corresponds to the post-compensation case at the receiver side.

To evaluate the performance of the I/Q imbalance model, the normalized mean squared error (NMSE) is used,² which is defined as

$$\text{NMSE[dB]} = 10 \log_{10} \frac{E[|x(n) - \hat{x}(n)|^2]}{E[|x(n)|^2]}. \quad (11)$$

Table I shows the performance of the different methods in model validation. The results illustrate that the dual-input nonlinear model has the best performance. In Case B), compared with the linear FIR filters proposed in [22], the linear equalizer in [23], and the nonlinear equalizer [9], the performance improvement of the proposed approach is around 4, 4.3, and 1 dB, respectively. This shows that there exist some nonlinearities in the I and Q branches and nonlinear imbalance between two branches that cannot be compensated for by using linear approaches. In Case A), the proposed method also shows the best performance. The nonlinear equalizer method shows worse performance when the modulator has significant I/Q imbalance. This shows that the nonlinear equalizer method cannot compensate for the I/Q imbalance, but only the nonlinear distortion in each branch. In both cases, it clearly shows that the nonlinearities in the I and Q branches and the nonlinear imbalance affect the quality of the transmitted signal severely.

Table I also shows the number of coefficients for different methods. The proposed method has more coefficients than the nonlinear equalizer. However, the computational load is almost the same since the nonlinear equalizer model has complex coefficients, while the proposed method only contains real coefficients. It should be noted that the performances of the linear FIR filter and linear equalizer models are saturated with the number of coefficients given, i.e., adding more coefficients will not improve the results.

According to system identification theory, in order to avoid over-fitting and uncertainty in the estimated kernels, the size of the data set should be at least 20 times the number of the estimated parameters [25]. In this study, the size of the data set

TABLE II
NMSE VERSUS ITERATION FOR PROPOSED DUAL-INPUT NONLINEAR MODEL

Iteration number	1	2	3	4
NMSE [dB]	-48.49	-49.34	-49.45	-49.41

is 20 000 samples, and is large enough compared to the number of coefficients.

B. I/Q Pre-Compensator Performance Evaluation

After verifying different models, these models are used as pre-compensators. As mentioned in Section III, in order to obtain robust estimations of model kernels, adaptive training is needed. A damped Newton algorithm [26] is used. For the proposed model, the NMSE versus the iteration number is shown in Table II, and it is noticed that the algorithm converges very fast in this study.

The final updated kernels are used to construct the I/Q pre-compensator. The original baseband signal is first pre-compensated before it is downloaded to the VSG. Table I shows the performance of the different approaches in pre-compensation. Clearly, the proposed dual-input nonlinear model has the best performance in both Cases A) and B).

Fig. 6 shows the power spectrum of the errors between the received signal $y(n)$ after pre-compensation and the original input signal $x(n)$. This figure shows that, without any compensation scheme, the in-band error between the measurement and the original I/Q data is quite large. This implies that there is severe distortion originating from the modulator impairments. Furthermore, it is worth mentioning that the nonlinear equalizer method cannot compensate the distortion in Case A) since the artificially introduced I/Q imbalance dominates the nonlinearities in each channel. For both cases, the proposed dual-input nonlinear model has the smallest in-band and out-of-band errors.

The differences between model validation and pre-compensation results using the proposed dual-input nonlinear model are very small, as shown in Table I. This verifies that the pre-compensation scheme shown in Fig. 4 can be effectively used for minimizing the nonideal effects in practical I/Q modulators.

It should be noted that wider signal bandwidths and/or stronger nonlinear characteristics may require longer memory depths and higher nonlinear orders to maintain high modeling accuracy. In consequence, the number of coefficients in the dual-input nonlinear model grows rapidly and may become computationally impractical. This can be overcome by applying

²For pre-compensation results, $y(n)$ is used instead of $\hat{x}(n)$.

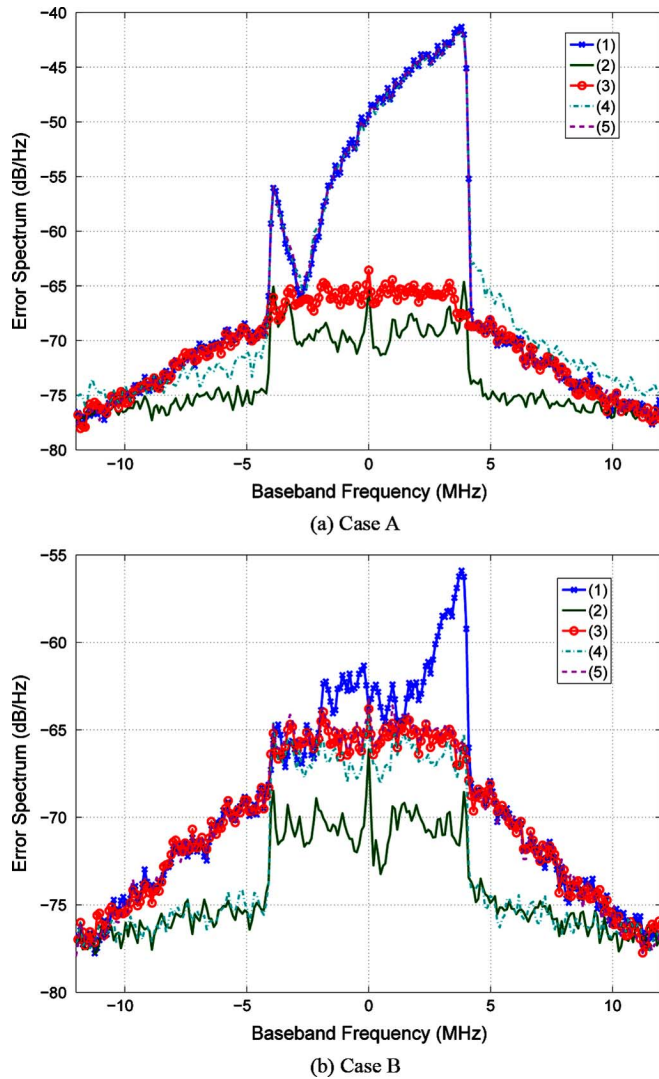


Fig. 6. Power spectrum of errors after pre-compensation. (1) Without compensation. (2) Proposed dual-input nonlinear model with nonlinear order 3 and memory depth 4. (3) Linear FIR filters in [22] with 20 taps. (4) Nonlinear equalizer in [9] with nonlinear order 3 and memory depth 4. (5) Linear equalizer [23] with 20 taps.

different kinds of Volterra-series-based reduction schemes such as the memory-polynomial [27] or dynamic deviation reduction-based Volterra series [15]. The same modeling approach can then be used for higher nonlinear orders and longer memory depths while maintaining reasonable complexity.

V. CONCLUSIONS

In this paper, a dual-input nonlinear model based on a real-valued Volterra series has been proposed to model and compensate for nonlinear frequency-dependent I/Q imbalance in RF modulators. The inverse model is used to construct an I/Q pre-compensator that is used for pre-compensation of the original baseband I/Q data. The performance was evaluated by experiments with a simple measurement setup. The experimental results have shown that the proposed I/Q imbalance model outperforms other previously published compensation techniques by including nonlinear frequency-dependent cross terms between

the I and Q branches. Therefore, the proposed approach can play an important role in improving the performance of current and future communication systems.

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Haiying Cao received the B.E. degree in communication engineering from Beijing University of Posts and Telecommunications, Beijing, China, in 2005, the M.Sc. degree in communication engineering from Chalmers University of Technology, Göteborg, Sweden, in 2007, and is currently working toward the Ph.D. degree at Chalmers University of Technology.

His research interests include advanced digital signal processing in wireless communication systems, behavioral modeling for RF power amplifiers, and nonlinear system identification algorithms.



Ali Soltani Tehrani received the B.Sc. degree in communication engineering from the K. N. Toosi University of Technology, Tehran, Iran, in 2005, the M.Sc. degree in communication engineering from Chalmers University of Technology, Göteborg, Sweden, in 2007, and is currently working toward the Ph.D. degree at Chalmers University of Technology.

His research interests currently include utilizing signal processing techniques for hardware impairments, power amplifier behavioral modeling and linearization, and high-efficiency transmitter

architectures.



Christian Fager (S'98–M'03) received the M.Sc. and Ph.D. degrees in electrical engineering and microwave electronics from Chalmers University of Technology, Göteborg, Sweden, in 1998 and 2003, respectively.

He is currently an Assistant Professor with the Microwave Electronics Laboratory, Chalmers University of Technology. His research interests are in the areas of large-signal transistor modeling and high-efficiency transmitter architectures.

Prof. Fager was the recipient of the 2002 Best Student Paper Award presented at the IEEE Microwave Theory and Techniques Society (IEEE MTT-S) International Microwave Symposium (IMS).



Thomas Eriksson was born in Skövde, Sweden, on April 7, 1964. He received the M.Sc. degree in electrical engineering and Ph.D. degree in information theory from Chalmers University of Technology, Göteborg, Sweden, in 1990 and 1996, respectively.

From 1997 to 1998, he was with AT&T Laboratories—Research. From 1998 to 1999, he was involved with a joint research project with the Royal Institute of Technology and Ericsson Radio Systems AB. Since 1999, he has been an Associate Professor with Chalmers University of Technology. His research

interests include communication, vector quantization, speaker recognition, and system modeling of nonideal hardware components.



Herbert Zirath (S'84–M'86–SM'08) was born in Göteborg, Sweden, on March 20, 1955. He received the M.Sc. and Ph.D. degrees from Chalmers University, Göteborg, Sweden, in 1980 and 1986, respectively.

He is currently a Professor of high-speed electronics with the Department of Microtechnology and Nanoscience, Chalmers University. During 2001 he became the Head of the Microwave Electronics Laboratory, Chalmers University, which currently has 70 employees. He currently leads a group of

approximately 40 researchers in the area of high-frequency semiconductor devices and circuits. He also works on a part-time basis with Ericsson AB as a Microwave Circuit Expert. He has authored or coauthored over 300 papers in international journals and conference proceedings and one book. He holds four patents. His main research interests include InP-HEMT devices and circuits, SiC- and GaN-based transistors for high-power applications, device modeling including noise and large-signal models for field-effect transistor (FET) and bipolar devices, and foundry-related monolithic microwave integrated circuits (MMICs) for millimeter-wave applications based on both III–V and silicon devices.