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Modelling and Compensation of Power Amplifier Distortion for LTE Signals using Artificial Neural Networks

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Abstract— **In this paper, artificial neural networks (ANNs) are used for power amplifier (PA) modelling and distortion compensation for Long Term Evolution (LTE) signals. The model is based on a powerful nonlinear autoregressive with exogenous inputs (NARX) ANN architecture, which produces accurate results for different LTE signals, thus confirming the solution's adaptability.**

Keywords- artificial neural networks; power amplifier; Long Term Evolution;

I. INTRODUCTION

Wireless systems require high data rates to serve growing user demands which LTE aims to fulfill through capacity and spectral efficiency [1]. Capacity and spectral efficiency require linearity of components in the transmitter, which in turn limits energy efficiency. On the other hand, the transfer characteristic of the transmitter is highly nonlinear when used in an energy-efficient way. This is mostly due to the power amplifier's (PA's) inherent nonlinearity, but the I/Q modulator also contributes to the distortion. The transmitted signal is distorted, causing errors and limiting capacity and spectral efficiency.

Several ways have been developed to deal with this trade-off between capacity and energy efficiency, out of which digital predistortion (DPD) became prevalent due to its flexibility, simplicity and efficiency [2] - [6]. The idea of DPD is a rather simple one: one first has to model the distortions the transmitter introduces and then predistort the signal with the complete inverse. Thus, once the signal is predistorted in the DPD and subsequently distorted in the I/Q modulator and PA, it comes out distortion-free. Researchers have used this technique extensively [2] - [6], developing predistortion methods for PA [2], [3], and for joint PA and I/Q modulator effects [4] – [6]. Although the PA causes most of the distortion in the transmitter because of its nonlinearity, added I/Q modulator impairments can significantly degrade the performance of DPD developed to deal with PA nonlinearity only [7], [9] – [11]. Hence, joint impairments models are generally preferable to two-step solutions. However, after developing successful linearization of joint impairments, verification should be done for PA distortion only. This serves as an independent litmus test of model generality, as well as presenting the use case scenario of a transmitter with an almost ideal I/Q modulator.

Therefore, in this paper, we test the proposed artificial neural networks (ANN) model from [6] further, by first modelling and then compensating for PA distortion only, without I/Q modulator imbalances. Tests were done for experimentally acquired LTE signals of different bandwidths and centre frequencies, to assess the adaptability of the model. Moreover, a different view on ANNs modelling capability is provided by presenting signal statistics of the measured and predicted data, as an added evaluation metric.

The paper is organized as follows: section II describes the measurement setup, section III explains the ANN model used for PA distortion in this paper, whereas section IV presents PA modelling and compensation results, along with appropriate signal statistics. Section V concludes the paper.

II. MEASUREMENT SETUP

Data required for modelling were experimentally acquired using measurement equipment by Agilent Technologies (Fig.1). LTE signals were generated in baseband using MATLAB and subsequently fed into the Vector Signal Generator (VSG), MXG N5182A. The MXG signal generator performed digital to analogue conversion as well as upconversion to radiofrequency (RF). The RF analogue signal was fed to the PA's input and Vector Signal Analyzer (VSA) 4406A which performed downconversion to baseband. Agilent Distortion Suite Software was used to record the complex (real - I and imaginary – Q signal component) baseband signal, postprocessed in MATLAB.

Test signals used were 64QAM OFDM LTE signals of 3 MHz and 1.4 MHz bandwidth, modulated at 880 MHz and 2140 MHz carrier frequencies respectively. In total, three different test signals were used for this paper: 3 MHz signal at 1 dB compression point (P1dB), 3 MHz signal at 2 dB back-off

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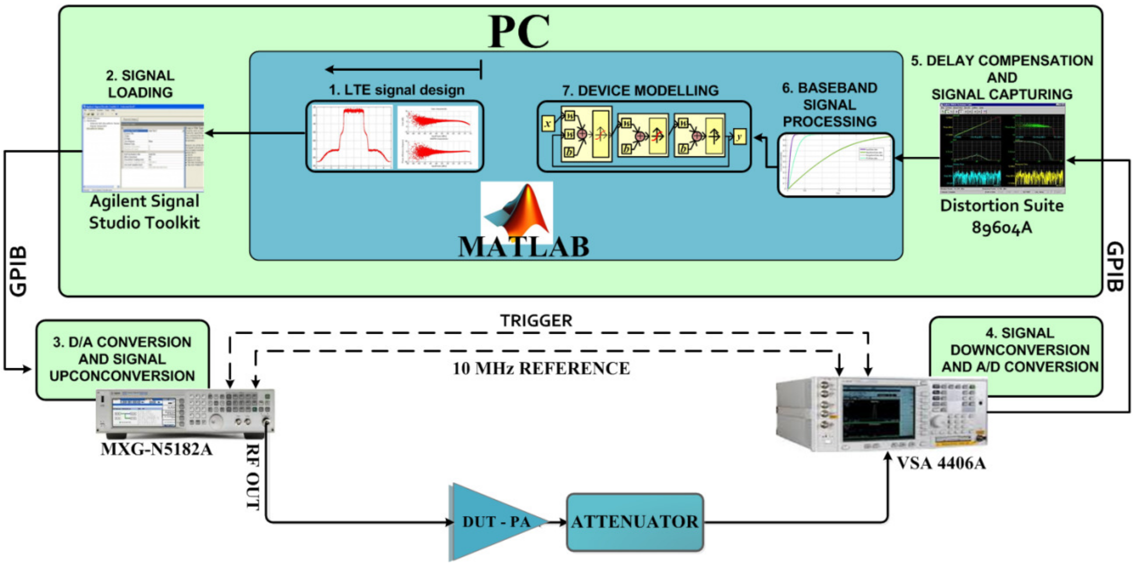

Figure 1. Measurement setup

from P1dB, and 1.4 MHz signal at 2 dB back-off from P1dB. The PA that served as a device-under-test (DUT) for experiments was the two-stages driver and CFH 2162-P3 (with 14 dB gain, 37 dBm P1dB). Data collection interval lasted 10 ms, gathering 100 000 data points with the sampling frequency of 10.24 MHz. Gathered data were divided into ANN training, validation (cross-validation) and test sets, needed for successful modelling, as explained in section III.

III. ANN MODEL

Since LTE specifies the use of different signal bandwidths and transmitting frequencies, an adaptable DPD solution is preferred. ANNs, with adaptability and universal approximation [8] as capabilities, have great potential for modelling nonlinear distortion [2] – [4], [6]. Hence, after developing joint impairments model in [6], we used the solution proposed and trained it for PA behavioural modelling with different LTE signals. The ANN used is a nonlinear autoregressive with exogenous inputs (NARX) [8] - essentially a time delayed feedforward ANN with feedback connections from the output at the input - allowing more powerful modelling by including both input and output memory elements. The parameters of the NARX model are as follows: number of neurons in the first and second hidden layer of 15 and 15; input and output memory depth of 2 and 5; activation function for the neurons in the hidden layers and output layer *tansig*, *tansig* and *purelin* respectively; and synaptic weight initialization interval of [-0.8, 0.8]. Levenberg–Marquard learning algorithm was employed for network training. Model generation and testing was done in MATLAB.

To measure the model's accuracy, normalized mean square error (NMSE) was used, together with power spectral density (PSD) graphs and amplitude-to-amplitude (AM-AM) and amplitude-to-phase (AM-PM) characteristics. A numerical degree of signal matching, NMSE, is defined as follows:

$$NMSE[dB] = 10\log_{10}\left(\frac{\sum_{i=1}^{N}[(I-I_{desired})^2+(Q-Q_{desired})^2]}{\sum_{i=1}^{N}(I_{desired}^2+Q_{desired}^2)}\right) \quad (1)$$

where I and Q stand for values of real and imaginary components of the signal produced by the ANN and $I_{desired}$ and $Q_{desired}$ for the target values collected in the measurement process.

Since the ANN uses time-domain signals to learn the component's behaviour, probability density function histograms for I and Q signal component amplitudes provide valuable insight in the accuracy of modelling, mostly in determining whether an ANN is favouring or discriminating certain ranges of magnitudes/amplitudes. In other words, in addition to the NMSE measure and PSD, AM-AM and AM-PM characteristics, these histograms can serve as indicators on how well different signal amplitudes were modeled. Hence, these are also included in section IV of this paper.

IV. RESULTS

Experimental results acquired with test equipment described in II, were used for modelling PA behaviour for 3 MHz and 1.4 MHz LTE signals at centre frequencies of 880 MHz and 2140 MHz, respectively.

For PA modelling with LTE 3 MHz signal at 880 MHz centre frequency and at 2 dB back-off from P1dB, NMSE value reached -38.91 dB. PSD graphs and AM-AM/PM characteristics show results in the spectral-domain (Figs.2-3), whereas the time-domain signal characteristics and the preservation thereof is shown in Figs.4-5.

The proposed direct model's performance was also tested using a 3 MHz LTE signal driven further into compression region, at P1dB exactly. NMSE deteriorated slightly (reaching -37.46 dB), achieving noticeable results in both time and spectral domain (Figs. 6-9) further demonstrating the model's adaptability.

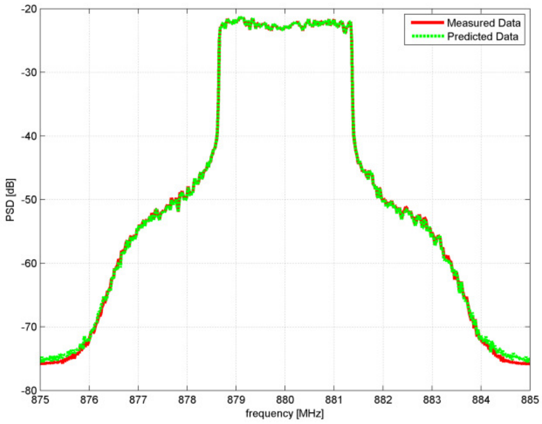

Figure 2. PSD characteristic of measured and predicted 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency

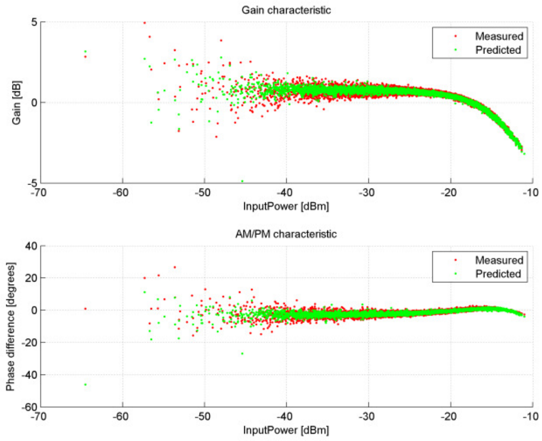

Figure 3. AM-AM/PM characteristics of measured and predicted 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency

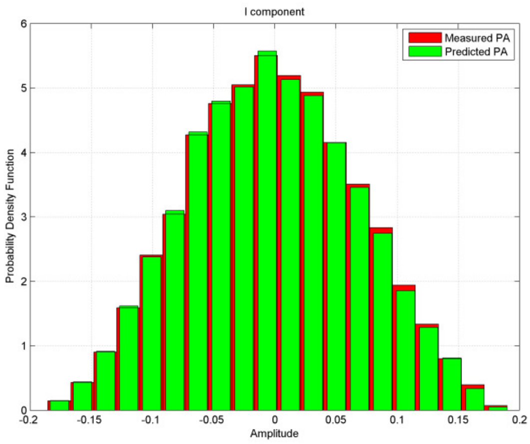

Figure 4. Amplitude histogram for measured and predicted 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency – I component

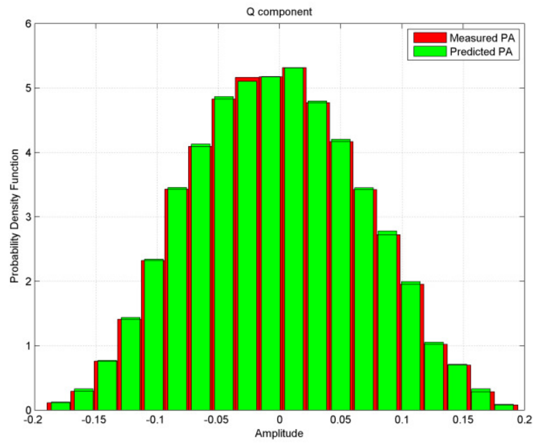

Figure 5. Amplitude histogram for measured and predicted 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency – Q component

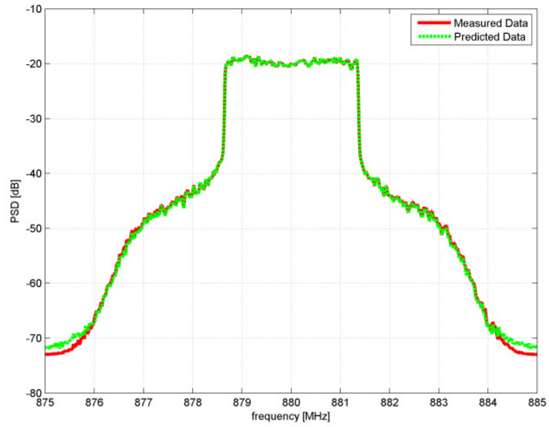

Figure 6. PSD characteristic of measured and predicted 3 MHz LTE signal at P1dB at 880 MHz centre frequency

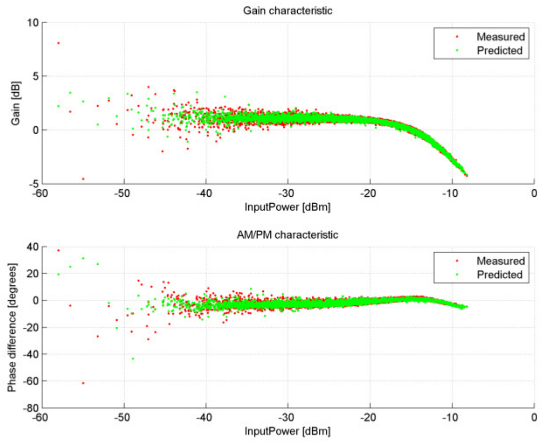

Figure 7. AM-AM/PM characteristics of measured and predicted 3 MHz LTE signal at P1dB at 880 MHz centre frequency

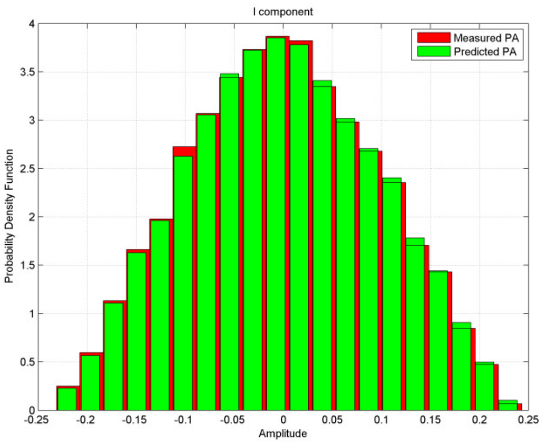

Figure 8. Amplitude histogram for measured and predicted 3 MHz LTE signal at P1dB at 880 MHz centre frequency – I component

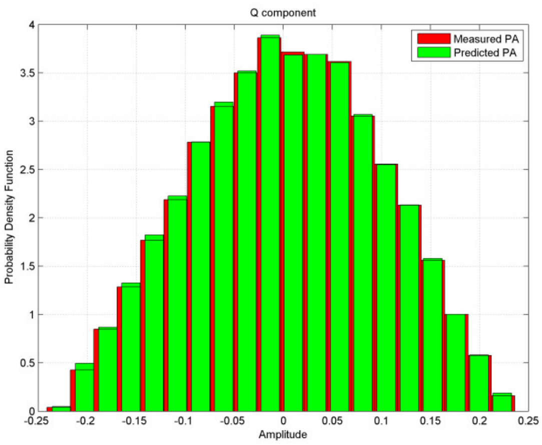

Figure 9. Amplitude histogram for measured and predicted 3 MHz LTE signal at P1dB at 880 MHz centre frequency – Q component

To further evaluate the adaptability of the model, we also tested it using LTE 1.4 MHz signal at centre frequency of 2140 MHz, achieving NMSE value of -33.79 dB. PSD graph as well as AM-AM/PM characteristics are shown in Figs.10-11. Amplitude histograms are portrayed in Figs.12-13.

Lastly, the DPD model was attained by mirroring the proposed direct (PA) structure. Linearization tests were conducted by concatenating the DPD with the PA structure. The DPD model was developed for LTE 3MHz signal at 2 dB back-off from P1dB at 880 MHz centre frequency. Achieved NMSE of linearization (calculated between the original input and the linearized signal) was -37.8 dB. The PSD graph of the DPD+PA cascade and AM-AM and AM-PM characteristics are shown in Figs.14-15.

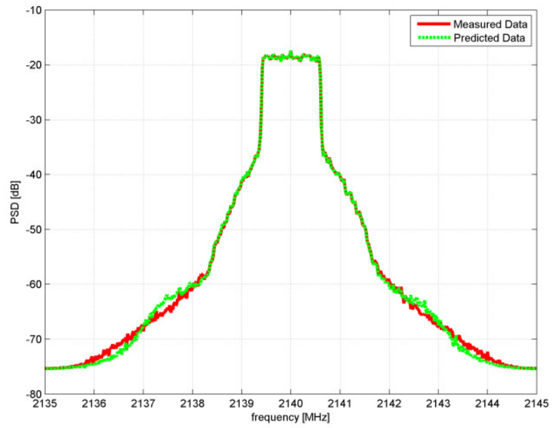

Figure 10. PSD characteristic of measured and predicted 1.4 MHz LTE signal at 2 dB back-off from P1dB at 2140 MHz centre frequency

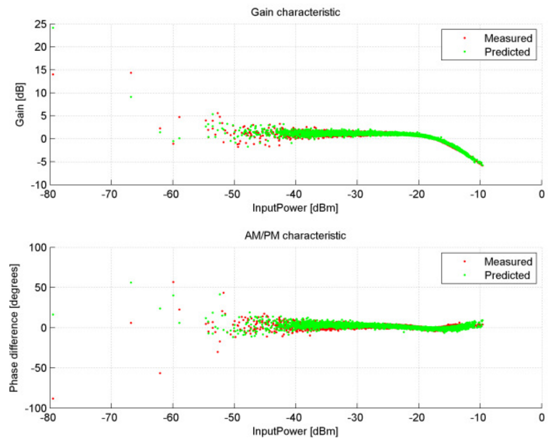

Figure 11. AM-AM/PM characteristics of measured and predicted 1.4 MHz LTE signal at 2 dB back-off from P1dB at 2140 MHz centre frequency

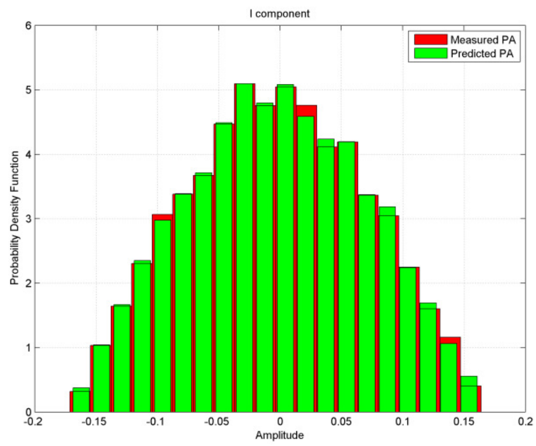

Figure 12. Amplitude histogram for measured and predicted 1.4 MHz LTE signal at 2 dB back-off from P1dB at 2140 MHz centre frequency – I component

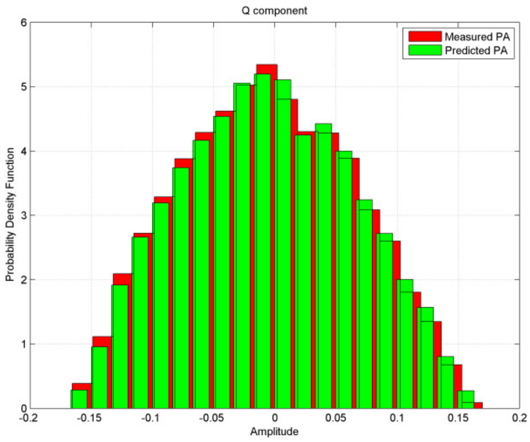

Figure 13. Amplitude histogram for measured and predicted 1.4 MHz LTE signal at 2 dB back-off from P1dB at 2140 MHz centre frequency – Q component

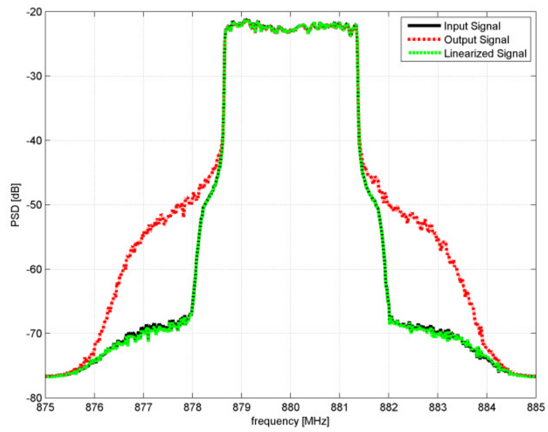

Figure 14. Linearization capability of DPD+DUT cascade in simulation for 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency- PSD characteristic

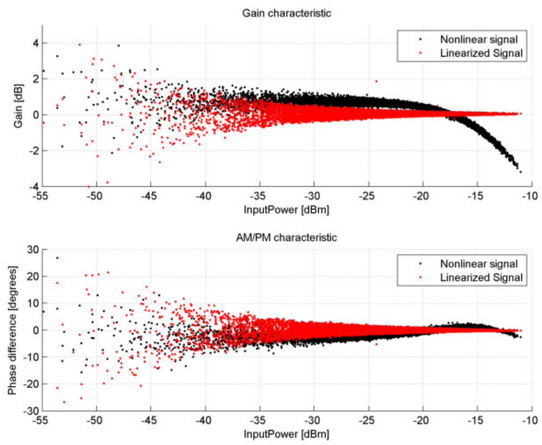

Figure 15. Linearization capability of DPD+DUT cascade in simulation for 3 MHz LTE signal at 2 dB back-off from P1dB at 880 MHz centre frequency - AM-AM/PM characteristics

V. Conclusion

In this paper we tested an ANN NARX model from our previous paper [6] further for PA distortion in LTE transmitters. Obtained results confirm the accuracy of the model for signals with different bandwidth, input power and centre frequency, verifying its adaptability. Through simulations, we also achieved linearization of the transmitted signal by predistortion. The results show that the solution proposed can also be efficiently used for applications where the branch imbalances introduced by the I/Q modulator are insignificant, thus making the solution generally applicable. As an additional evaluation of the model's capabilities, we presented signal statistics probability density function histograms for time-domain signals that show a high level of matching, which is concurrent with other accuracy measures used such as NMSE and PSD and gain/phase characteristics graphs.

References

[1] E. Dahlman, S. Parkvall, J. Sköld, 4G LTE/LTE-Advanced for Mobile Broadband. 1st ed. Oxford: Elsevier, 2011.

[2] M. Rawat, K. Rawat, F.M. Ghannouchi, "Adaptive Digital Predistortion of Wireless Power Amplifiers/Transmitters Using Dynamic Real-Valued Focused Time-Delay Line Neural Networks," IEEE Transactions on Microwave Theory and Techniques vol. 58(1), pp. 95-104, January 2010.

[3] F. Mkadem, S. Boumaiza, "Physically Inspired Neural Network Model for RF Power Amplifier Behavioral Modeling and Digital Predistortion," IEEE Transactions on Microwave Theory and Techniques, vol. 59(1), pp. 913–923, April 2011.

[4] M. Rawat, F.M. Ghannouchi, "A Mutual Distortion and Impairment Compensator for Wideband Direct-Conversion Transmitters Using Neural Networks," IEEE Transactions on Broadcasting, vol. 58(2), pp. 168–177, June 2012.

[5] L. Anttila, P. Händel, M. Valkama, "Joint Mitigation of Power Amplifier and I/Q Modulator Impairments in Broadband Direct-Conversion Transmitters," IEEE Transactions on Microwave Theory and Techniques, vol. 58(4), pp. 730–739, April 2010.

[6] A. Anastasijevic, D. Coja, N. Neskovic, A. Neskovic, D. Budimir, "Joint power amplifier and I/Q modulator impairments modelling and compensation for LTE transmitters using artificial neural networks," International Journal of Electronics and Communications (AEÜ), vol. 69(2), pp. 529–538, February 2015.

[7] F. Gregorio, J. Cousseau, S. Werner, T. Riihonen, R. Wichman, "Compensation of I/Q Imbalance and Transmitter Nonlinearities in Broadband MIMO-OFDM," IEEE International Symposium on Circuits and Systems (ISCAS), pp. 2393-2396, May 2011.

[8] S. Haykin, Neural Networks: a comprehensive foundation, 2nd ed. London: Prentice-Hall, 1999.

[9] L. Ding, Z. Ma, D.R. Morgan, M. Zierdt, G.T. Zhou, "Frequency-Dependent Modulator Imbalance in Predistortion Linearization Systems: Modeling and Compensation," Conference Record of the Thirty-Seventh Asilomar Conference on Signals, Systems and Computers, pp. 688-692, 2004.

[10] L. Ding, Z. Ma, D.R. Morgan, M. Zierdt, G.T. Zhou, "Compensation of Frequency-Dependent Gain/Phase Imbalance in Predistortion Linearization Systems," IEEE Transactions on Circuits and Systems vol. 55(1), pp. 390-397, February 2008.

[11] J.K. Cavers, "New Methods for Adaptation of Quadrature Modulators and Demodulators Amplifier Linearization Circuits," IEEE Transactions on Vehicular Technology, vol. 46(3), pp. 707–16, August 1997.