The Application of Globally Recurrent Neural Networks for Modelling of LNAs for LTE Systems

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Abstract – **In this paper, a behavioural model of low-noise amplifiers, intended for LTE receivers is presented. The model is based on a globally recurrent artificial neural network. It has been developed for the Mini Circuit ZFL-500 LNA. The measured data of the device has been used for the model development and verification in the MATLAB software environment. The input signal is an LTE signal with 3MHz channel bandwidth and carrier frequency of 1960MHz. Good agreement between the modelled and measured output signal proves the model high accuracy.**

Keywords – **Artificial neural networks, behavioural modelling, low noise amplifier, Long Term Evolution.**

I. Introduction

Nowadays, mobile communication systems are developing and growing faster than before. Due to the increasing demands, advanced wireless systems standards should provide new and better services, operating with lower power consumption, better performances, and lower cost.

Mobile communication systems are moving rapidly through a series of generations. The 2.5 generation was the first one that enabled the mobile Internet access, followed by 3G with further improvements in broadband data transmission. Both 2.5G and 3G mobile systems process voice and data through two separate domains. Although 3G systems support TCP/IP traffic, they are not fully IP oriented. The need for high speed internet services support in mobile communications led to a new fully IP-oriented standard called Long Term Evolution - LTE [1]. The improved version of LTE, named “LTE Advanced” is a 4G (fourth generation) standard for mobile communications developed by 3GPP (3rd Generation Partnership Project) [2], allowing a high data rate transmission over radio interface. The specifications were defined in 3GPP Release 8 and its implementation started in 2009 [3].

Due to the high requirements defined for the LTE standard, it is necessary to provide transmitters and receivers with corresponding high performances [4]. One of these performances relates to their linearity level, and therefore a lot of research has been devoted to the development of the linearization techniques for amplifiers, having in mind that the amplifiers have the strongest influence to the transmitter/ receiver linearity. Usually, the term linearization is linked to the concept of power amplifiers and most of the research has been devoted to linearization of power amplifiers [5], [6]. On the other hand, the linearity of the receiving part is of great importance, because any nonlinearity of the receiver can cause problems in signal processing.

As it is well known, distortions in most RF circuit blocks arise from the nonlinearities inherent in the devices used. The first and the most important block in the receiver is a low noise amplifier (LNA), which must provide sufficient amplification of the received signals with minimal noise addition. On the other hand, LNAs, like all amplifiers, shows non-linear behaviour at a certain power level. A problem may appear when some of interfering signals on the receiver side are at a level high enough to put the low noise amplifier in its non-linear operating region. Due to the mentioned, there is a need to develop a technique for low-noise amplifier linearization, and lately some research has been carried out with that aim [7].

One of the most commonly used techniques for amplifier linearization in the LTE systems is the digital pre-distortion technique (DPD) [8]. The pre-distortion circuit has inverse gain and phase characteristics comparing to the amplifier and combined with the amplifier improves the system linearity. Basically, the “inverse amplifier distortion” is introduced to the input of the amplifier, thereby cancelling any non-linearity that the amplifier might have. The DPD is usually applied for linearization of the power amplifiers on the transmitter side [9], [10]. As already mentioned, the linearity of the receiver is very important as well, but a relatively small number of studies has been focused to this topic [11].

The first step in the DPD implementation is the development of an amplifier behavioural model that should predict the actual behaviour of the considered amplifier. The behavioural model can be developed using various mathematical approaches. Accordingly, some of frequently used models are: the Volterra model [12], the memory polynomial model [13], the Wiener model [14], and the Hammerstain model [15].

Moreover, an amplifier behavioural model can be based on application of artificial neural networks (ANNs). There are a few papers reporting low noise amplifier models based on ANNs [16], [17]. The ANNs represent a powerful modelling tool in the field of RF and microwave circuits [18-23]. Among others, the ANN approach has been widely used for modelling of power amplifiers [24-28]. Recently, behavioural models of a low noise amplifier, intended for LTE receiver-end, have been developed by the authors of this paper [29-31]. However, the memory effects of the amplifier are not always linked only to the input signal, but also to the output signal, and in that case for the amplifier behavioural modelling the most appropriate neural network is neural network with recurrence. In this paper, a behavioural model of a low noise amplifier

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based on a globally recurrent neural network will be presented.

In Section II, a brief concept of the used ANNs is provided. In Section III the proposed neural network model is described, while in Section IV the validation of the proposed model is presented. In Section V the main results are summarized.

II. Artificial Neural Networks

Artificial neural networks can be defined as parallel computing systems made up of a certain number of simple, highly interconnected processing elements, neurons. Neurons are typically organized into layers, of which the first one is called input layer, the last one is called output layer, and all layers between them are called hidden layers. An ANN can contain at least one, or more hidden layers. A relation between the inputs and the output of each neuron is defined by its transfer function. Each connection between neurons is weighted.

ANNs can be trained to learn any dependence between the input and the output data. During the training procedure, the ANN parameters, connection weights and thresholds of the neuron transfer functions, are determined. The training is carried out in the way to provide the smallest possible difference between the actual and desired values of the ANN output. After training, the ANN should be capable to generate correct output signals for the input signals that were not presented during training (generalization ability).

The most often used type of neural networks is MultiLayer Perceptron Neural Network (MLP). The MLP is a feed-forward neural network without any feed-back connections, wherein the output of each neuron from one layer is directly fed to the input of all neurons in the next layer, Fig. 1.

The input-output relationship of the MLP network is:

$$y(t) = f(x(t)), \tag{1}$$

where $x(t)$ is the input signal at the moment t, $y(t)$ is the output signal at the moment t.

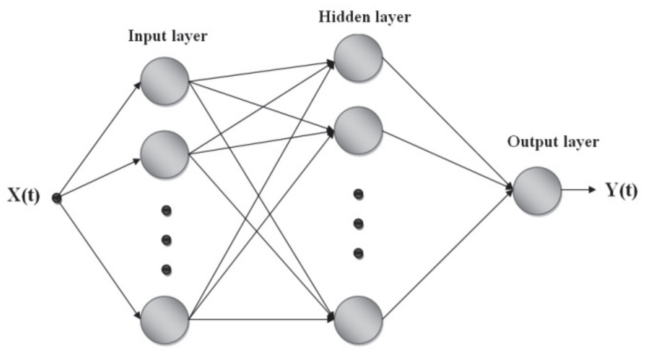


Fig. 1. The MLP neural network architecture

Although, the MLP represents the most prominent and well researched class of ANNs, the MLP cannot approximate non-linear systems having memory effects with a satisfactory accuracy.

Therefore, for the modelling of nonlinear systems with memory, some other types of networks are needed. The most commonly used type of neural network for that kind of modelling is a Time Delay Neural Network (TDNN) [24], [25], [34]. At the input of a TDNN, in addition to the current signal value, there are its several time-delayed values. A simplified architecture of TDNNs is shown in Fig. 2. In the case of TDNN, the memory effects of the modeled system are introduced in the model by including delayed input signal among the inputs.

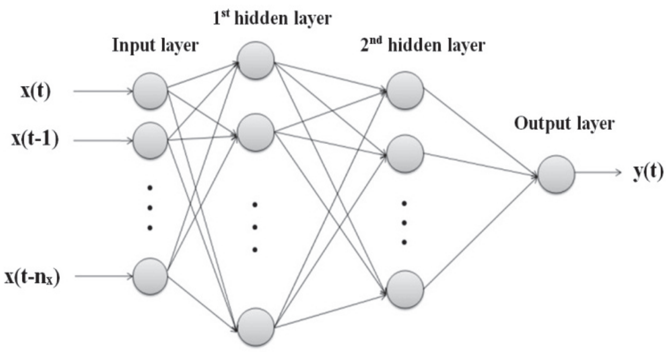


Fig. 2. The feedforward TDNN architecture

The input-output relationship of the TDNN network is:

$$y(t) = f(x(t), x(t-1), ..., x(t-n_x)), \tag{2}$$

where $x(t)$ is the input signal at the moment t, $y(t)$ is the output signal at the moment t, and n_x is the number of delayed input signals.

However, in some cases, the behavioural modelling by using a simple TDNN network does not give satisfactory results, because memory effects are not always linked only to the input signal, but also to the output signal. Therefore, neural network with one or more delayed output signals should be employed. Neural networks that include that kind of feedback loop (recurrence) are called recurrent neural networks. The recurrence in neural network can be local or global. If the recurrence refers to the inner layers of the network then it is called local recurrence [33]. On the other hand, if the recurrence refers to the output layer, then it is called global recurrence [32]. In this paper, a type of dynamic network containing global recurrence, called the Globally Recurrent Neural Network (GRNN) will be introduced.

Globally recurrent neural networks can achieve very high accuracy in modelling of non-linear systems with memory. Also, in most cases, globally recurrent networks converge faster and generalize better than neural networks without recurrence.

The architecture of a globally recurrent network is presented in Fig. 3 where TDL (time delay line) blocks are used for representing time-delayed input and output signals.

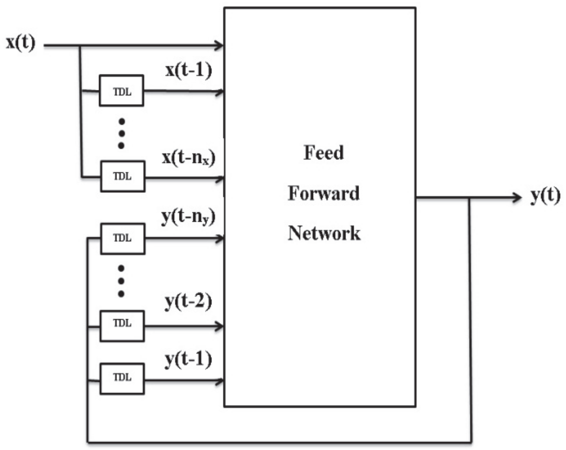


Fig. 3. Architecture of a globally recurrent network

The defining equation for the globally recurrent model is:

$$y(t) = f(x(t), x(t-1),..., x(t-n_x), y(t-1),..., y(t-n_y)), \quad (3)$$

where $x(t)$ is the input signal at the moment t, $y(t)$ is the output signal at the moment t, n_x is the number of delayed input signals and n_y is the number of delayed output signals.

As it can be concluded from Eq. 3, the output of the globally recurrent network depends on the current input and output signals, and one or more theirs delayed values.

The delayed output signals can be fed to the input of the network on two different manners. The first one is to fed the neural network output directly from the output to the input of network (parallel architecture), Fig. 4a). As this architecture assumes complex dynamics procedures for the training, an alternative architecture (series-parallel), Fig. 4b), is used during the training phase having in mind that in that case the static backpropagation algorithm can be applied.

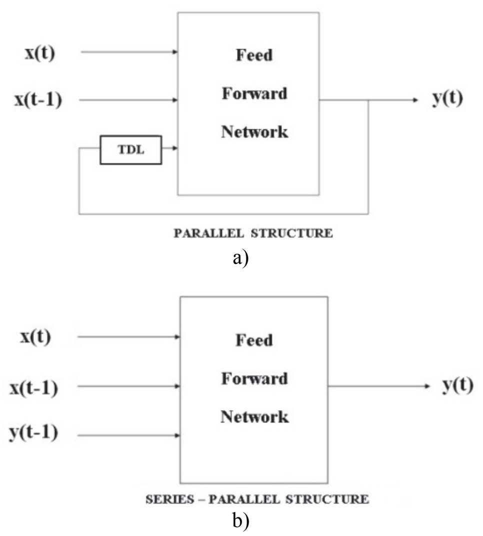


Fig. 4. Two types of the recurrent architecture (for simplicity, $n_x = n_y = 1$)

III. THE PROPOSED NEURAL NETWORK MODEL

The neural network model based on globally recurrent ANNs has been developed for the purpose of the modelling of the low-noise amplifier Mini Circuit ZFL-500. The neural network model development was performed in the MATLAB software environment. The data needed to train and test the model have been obtained by measurements of the input and output signals of the low noise amplifier. The input signal, typical for 4G, has been generated in MATLAB and brought through the signal generator MXGN5182A to the input of the considered amplifier. It is an OFDM (Orthogonal Frequency Division Multiplexing) signal with the carrier frequency of 1960 MHz and 3 MHz wide channel, which corresponds to the LTE specifications. The amplifier output signal has been measured by using a vector signal analyzer, where has been recorded on a computer in MATLAB format via software VSA Suite 89604, Fig. 5.

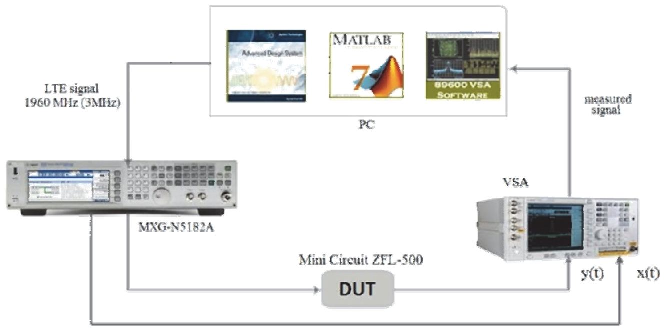


Fig. 5. The measuring procedure of the amplifier's input and output signals

Since both input and output measured signals have complex values, they are separated into two signal components: in phase components I_{IN}, I_{OUT} and quadrature components Q_{IN}, Q_{OUT} as given by equations (4) and (5):

$$X(t) = I_{IN}(t) + j * Q_{IN}(t), \quad (4)$$

$$Y(t) = I_{OUT}(t) + j * Q_{OUT}(t). \quad (5)$$

As mentioned earlier, the series-parallel architecture has been used for the network training, Fig 6.

The ANN is aimed to model the following relationship:

$[I_{OUT}, Q_{OUT}] = f\ (I_{IN}(t), Q_{IN}(t), I_{IN}(t\text{-}1), Q_{IN}(t\text{-}1),...,I_{IN}(t\text{-}n_x), Q_{IN}(t\text{-}n_x), I_{OUT}(t\text{-}1), Q_{OUT}(t\text{-}1),..., I_{OUT}(t\text{-}n_y), Q_{OUT}(t\text{-}n_y))$(6)

where n_x denote the memory depth of the input and n_y denote the memory depth of the output signals, i.e. the number of delayed input and output signal samples. From Eq.6 it can be concluded that beside in phase and quadrature components of the amplifier input signal, I_{IN} and Q_{IN}, and theirs delayed values on the network input, there are also delayed values of in phase and quadrature components of the output signal, I_{OUT} and Q_{OUT}, Fig. 6.

From the available measured data three sets have been formed: training, validation and test sets, having 30,000, 5,000 and 15,000 samples, respectively. It is important to emphasize that sets contain different samples of signal and there is no samples overlapping. This distribution of the samples was adopted in order to avoid the problem of over-fitting, and to maximize the network generalization.

The training and the validation set have been used during the training, while the test set has been used for estimating the accuracy of the trained ANN.

During the training process optimization of the following network parameters was performed: number of layers, number of neurons in the hidden layers, and memory depth. It should be noted that after the ANNs are trained, their parallel configuration with the closed loop (the parallel structure), Fig. 4a) is used for further validation of their accuracy.

Analysis of the test results according to the normalized mean squared error (NMSE), Eq. 7, has shown that the best solution is a two-layered globally recurrent having 12 and 5 neurons in the first and the second hidden layer, respectively. The network with a memory depth equal to 1, for the both input and output signals, has been chosen, having in mind that by further increasing of memory depth no significant improvement of the accuracy has been achieved.

The normalized mean squared error, $NMSE_{db}$, is defined as:

$$NMSE_{dB} = 10log_{10}\left(\frac{\sum_{i=1}^{n}\left|Y_{measured}(i) - Y_{modelled}(i)\right|^2}{\sum_{i=1}^{n}\left|Y_{measured}(i)\right|^2}\right), \quad (7)$$

where $Y_{measured}$ is the measured output signal of amplifier, $Y_{modelled}$ is the output signal obtained by the neural network, and n is the number of samples in the observed test set. The $NMSE_{db}$ achieved by the proposed model is -58dB, which can be considered as a very good result.

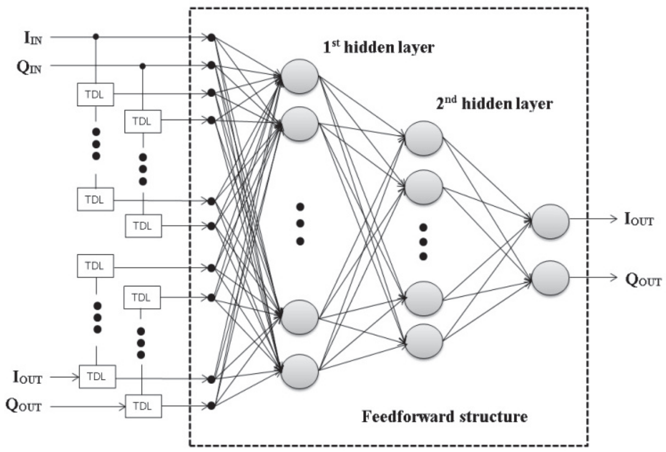


Fig. 6. The proposed globally recurrent neural network LNA model (series-parallel representation)

IV. Model Validation

In order to confirm the accuracy of the proposed model, the signal measured at the output of the amplifier and the output signal modeled by the neural network have been compared, both in the frequency and the time domain. It is important to highlight that the comparison refers to the signals not used during the training phase.

Agreement in the frequency domain has been examined through the Power Spectral Density (PSD) function. The comparison of the PSD function of the measured signal and the PSD function of the signal generated by the proposed model is shown in Fig. 7. The PSD function of the signal generated by the globally recurrent neural network is displayed by red stars, while the blue line corresponds to the PSD function of the measured output signal. It can be concluded that PSD shows excellent agreement through the whole frequency channel.

The model validity in the time domain has been checked by the comparison of simulation and measurement results for the I_{OUT} and Q_{OUT} components, AM/AM and AM/PM characteristics.

The simulated values of the I_{OUT} and Q_{OUT} components versus measured ones are given in Fig. 8. It can be noticed that for both components very good agreement of the measurements and simulations has been achieved.

The comparisons of the AM/AM and AM/PM characteristics of the measured signal and the output signal generated by the proposed model are shown in Fig. 9 and Fig. 10, respectively. The shown plots also confirm a good accuracy of the proposed model.

In order to validate the proposed neural network model for the linear region of work, the ANN model has been tested with a signal whose level is significantly lower than the level of the signal that is used during network training.

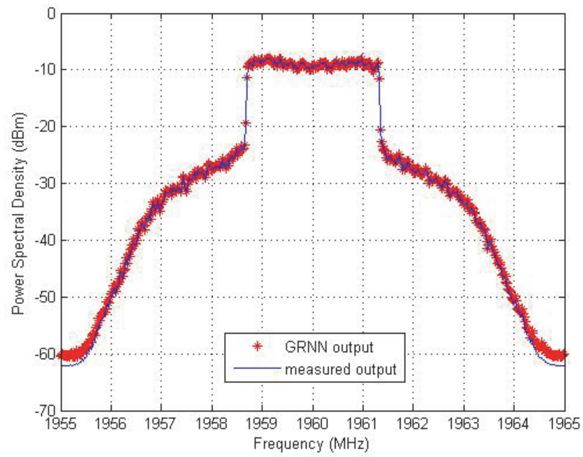
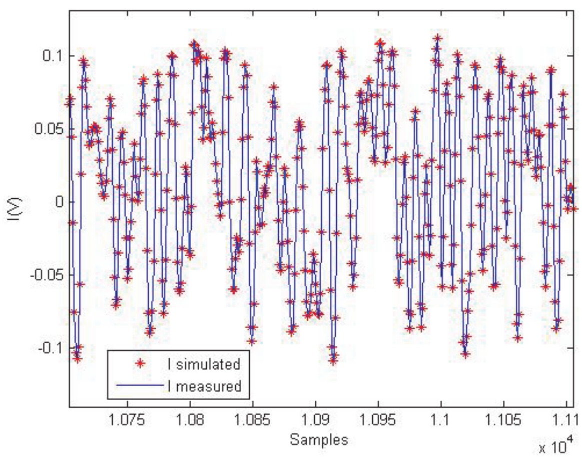
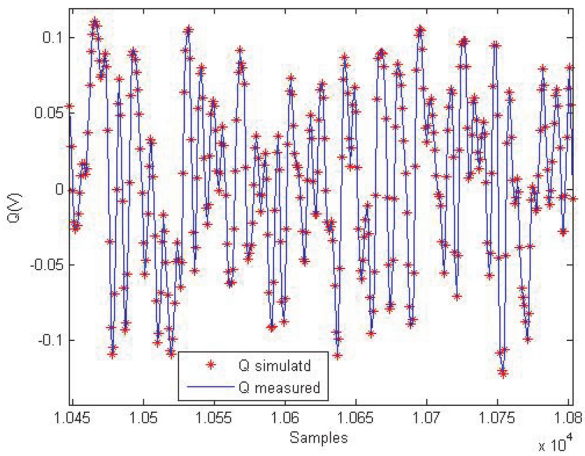


Fig. 7. The comparison of the power spectral density of the measured output signal and the globally recurrent neural network output signal



a)



b)

Fig. 8. The comparison of the simulated and measured amplifier output signal: a) in phase component b) quadrature component

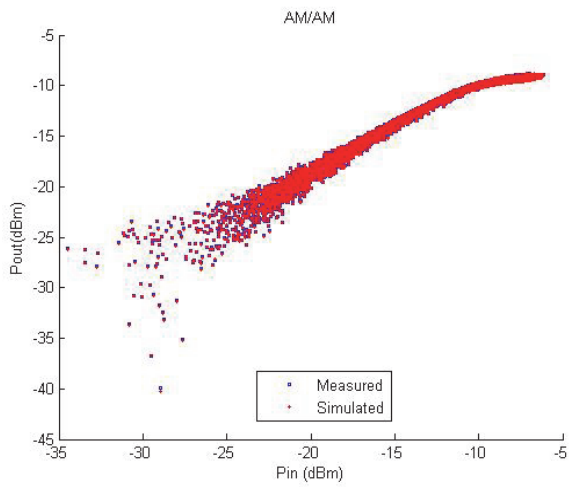


Fig. 9. The comparison of AM/AM characteristics of measured output signal and the globally recurrent neural network output signal

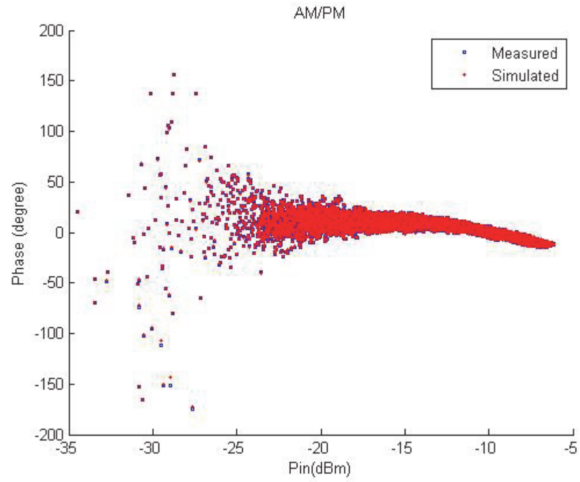


Fig. 10. The comparison of AM/PM characteristics of measured output signal and the globally recurrent neural network output signal

As it was done previously, the signal measured at the output of the amplifier and the output signal modeled by the neural network have been compared, both in the frequency and the time domain. Agreement in the frequency domain has been examined through the Power Spectral Density (PSD) function, Fig. 11. Similar to the previous case it can be noticed that PSD shows excellent agreement through whole frequency channel. The comparison of the simulated and measured I_{OUT} and Q_{OUT} components in time domain is shown in Fig.12, while the AM/AM and AM/PM characteristics are given in the Fig. 13 and Fig. 14, respectively. From Fig. 12 it can be noticed that for both components very good agreement of the measurements and simulations has been achieved. On the other hand the AM/AM and the AM/PM characteristics also prove the high accuracy, and good network generalization ability.

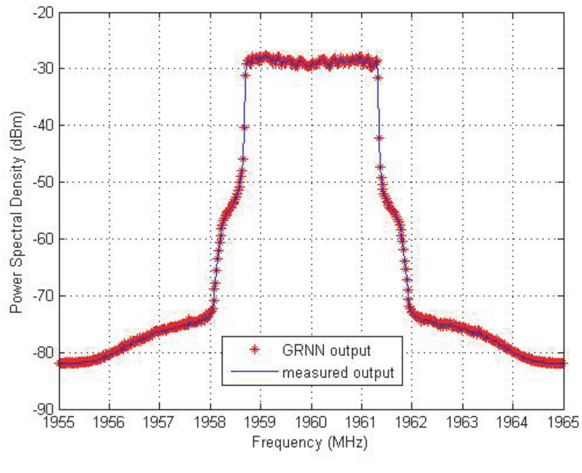
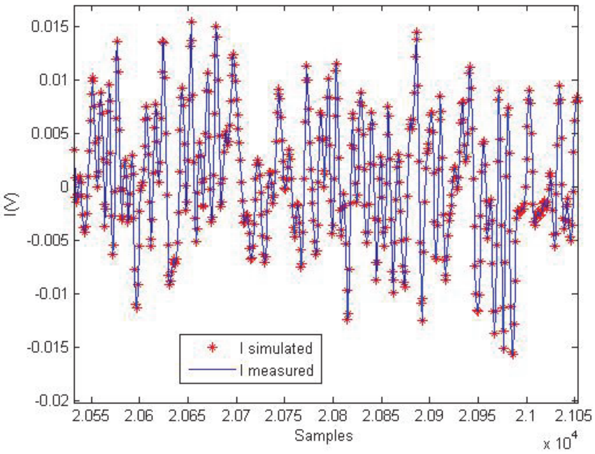
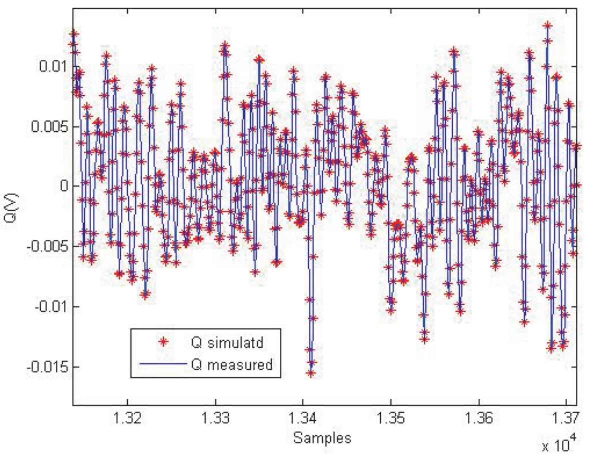


Fig. 11. The comparison of the power spectral density of the measured output signal and the globally recurrent neural network output signal (linear region)



a)



b)

Fig. 12. The comparison of the simulated and measured amplifier output signal: a) in phase component, b) quadrature component (linear region)

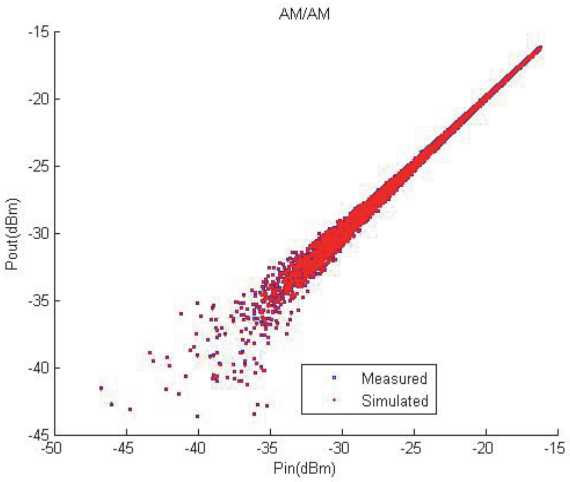


Fig. 13. The comparison of AM/AM characteristics of measured output signal and neural network output signal (linear region)

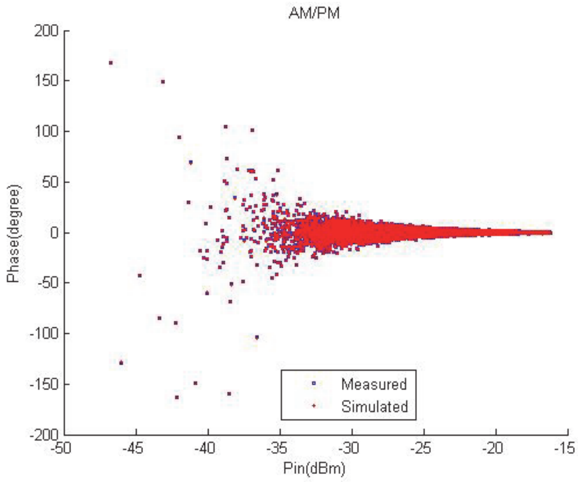


Fig. 14. The comparison of AM/PM characteristics of measured output signal and neural network output signal (linear region)

V. CONCLUSION

This paper introduces the behaviour modelling for low-noise amplifier intended for the receiving segment in LTE systems. Modelling has been performed in MatLab software environment by using two layered globally recurrent artificial neural networks. The proposed neural network model was tested according to the normalized mean squared error, and a very small NMSE of -58dB has been achieved. Also, the further analysis has shown a very good agreement between the simulated and measured PSD, AM/AM and AM/PM characteristics.

The network generalization ability has been also verified through the testing with signal which level is much lower than the level of the signal used in training phase. It was proven that the network accuracy is very high even for signals whose level is not close to the level of the signal used in training set. According to all results obtained by the model testing, it can be concluded that proposed neural network model is very convenient for the LNA behavioural modelling.

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