Performance Prediction of Power Amplifiers for the Extended Bandwidth via Neural Networks

Yapay Sinir Ağları Yoluyla Genişletilmiş Bant Genişliği için Güç Kuvvetlendiricinin Performans Tahmini
Performance Prediction of Power Amplifiers for the Extended Bandwidth via Neural Networks

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***Özetçe* —Bu bildiri, derin sinir ağı (DNN) yardımıyla Güç kuvvetlendirici (PA) modellenmesi için optimizasyon metodolojisini sunmaktadır. Bu yazıda, uzun kısa süreli bellek (LSTM) DNN'nin kullanıldığı PA'nın frekans tepkilerini tahmin etmeye yol açan etkileyici bir yaklaşım öneriyoruz. Sunulan yöntem, PA'yı saçılma parametreleri, kazanç, çıkış gücü ve verimlilik açısından doğru bir şekilde modeller. Bu yaklaşım, mühendis deneyimine bağımlılık sorununu ele alır ve geniş frekans bandı elde etmedeki zorlukları azaltır. Tüm modelleme süreci elektronik tasarım otomasyon aracı ve sayısal analizör kombinasyonu ile gerçekleştirilir ve otomatik ortam oluşturulur. Önerilen yöntemi doğrulamak için, bir PA tasarlanmış ve 1 ila 2,3 GHz frekans aralığı için modellenmiştir. DNN ilk önce bant genişliğinin yarısı için eğitilir ve daha sonra modellenen PA, genişletilmiş frekans bandını tahmin etmek için kullanılır.**

Anahtar Kelimeler—Derin sinir ağı (DNN), genişletilmiş frekans yanıtı, uzun kısa süreli bellek (LSTM), Güç kuvvetlendirici (PA), tahmin.

***Abstract*—This paper presents the optimization methodology for modeling the power amplifier (PA) with the aid of deep neural network (DNN). In this paper we propose an impressive approach leading to extrapolate frequency responses of the PA, where the long short-term memory (LSTM) DNN is employed. The presented method models the PA accurately in terms of scattering parameters, gain, output power and efficiency. This approach tackles the problem of dependency to the engineer experience and reduces the challenges in achieving large frequency band. All the modeling process is performed with the combination of electronic design automation tool and numerical analyzer where automated environment is created. For validating the proposed method, one PA is designed and modelled for the range frequency of 1 to 2.3 GHz. The DNN is firstly trained for the half of the bandwidth and later, the modeled PA is used for predicting the extended frequency band.**

Keywords—Deep neural network (DNN), extended frequency response, long short-term memory (LSTM), power amplifier (PA), predict.

I. Introduction

For the next generation networks, the overall performance of power amplifiers (PAs) plays an important role [1]. For these future high data-rate wireless systems, wideband, high-efficient and linear PAs are required [2], [3]. Hence, effectively modeling and sizing the adopted radio frequency (RF) devices require reliable methodologies [4]–[10].

Various methodologies are presented in the recently published studies based on the optimization. In [11], a linearity optimization is employed for enhancing the input third-order intercept point of amplifier. The bayesian optimization (BO) is used in [12] for designing a Doherty power amplifier where this method results in reduced design time consumption. From another point of view, the BO method is used with dynamic feasible region shrinkage technique [13] to enhance convergence speed of the PA design from circuit and electromagnetic (EM) viewpoint. Source/load pull impedance modeling is used in [14] to select suitable transistors, resulting in optimal gain and power-added efficiency. In [15] a systematic optimization approach is employed to identify the optimal impedance and design the matching networks from Smith chart. The coarse model is used in [16] leading to representing matching networks through rational polynomials. The particle swarm optimization method is employed in [17], [18] for designing complex designs such as Doherty amplifier.

In the recently published literature, artificial neural networks prove their effectiveness in modeling PA designs characterized by multiple concurrent parameters and design constrains [19]–[21]. Among various neural networks, deep neural networks (DNN) show the most successful results due to their reliable accuracy, paving the way of modeling through ANNs [22], [23]. This paper devotes to present the methodology for predicting the extended frequency responses of PA in terms of S_{11}, power gain (G_p), output power (P_{out}), and drain efficiency (η_D). For this case, an accurate DNN is trained for half of the targeted bandwidth. Afterwards, the constructed DNN is employed for predicting the remained half of bandwidth. The trained DNN is powerful enough in predic-

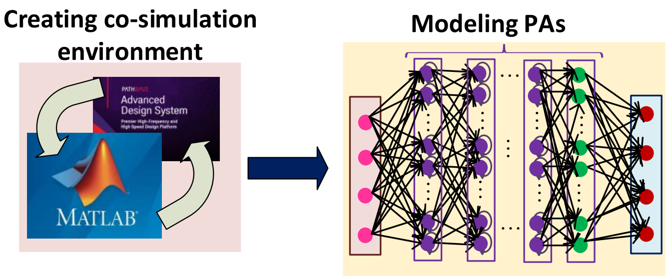

Figure 1: Flowchart of proposed method.

ting the larger frequency band; hence simulating/measuring the whole large frequency bandwidth will not be required. In our approach, long short-term memory (LSTM)-based DNN results in reducing the engineer's effort importantly. Figure 1 presents the general flowchart of proposed method. All the modeling is performed within the created co-simulation environment between keysight ADS and MATLAB as the electronic design automation (EDA) tool and numerical analyzer, respectively. The paper is organized as follows: Section II provides the descriptions around of presented methodology where Sec. III describes the practical implementation of proposed DNN. Section IV presents the achieved outcomes from the employed approach for the PA modeling. Finally, Sec. V concludes this study.

II. Proposed Methodology

Next-generation networks require wide-band design, characterized by multiple active and passive devices. Achieving modelling and design capability for the whole frequency band is not straightforward and requires additional effort, time, and memory. From another point of view, predicting the various design performances on a wider bandwidth can lead into better security. Recently, DNNs proved their reliability and feasibility in modeling microwave designs [24]. The model validity is based on the accuracy specification achieved from the constructed DNN. Fig. 2 presents the proposed long short term memory (LSTM)-based DNN for modeling the PAs leading to predict an extended frequency band.

For training the LSTM-based DNN, suitable amount of data can be achieved using parametric sweep where the design parameters of PA can be iterated randomly [22]. The employed DNN in this study is the regression DNN and the rule of thumb method is used for achieving the optimal hyperparameters of network such as number of hidden layers and number of neurons in each layer. As shown in Fig. 2, the DNN input layer specifications are S_{11}, G_p, P_{out}, and η_D for the frequency from f_1 to f_n. The output layer predicts the specification of input layer for the adjacent frequency band (from f_n to f_m). After training the DNN, the *'predictAndUpdateState'* is employed in the MATLAB environment for predicting the extended frequency band. In the trained DNN, the rectified linear unit (ReLU) function is employed as the activation function and also the normalized root mean square error (RMSE) is used for determining the convergence. Algorithm 1 presents the summary of proposed methodology.

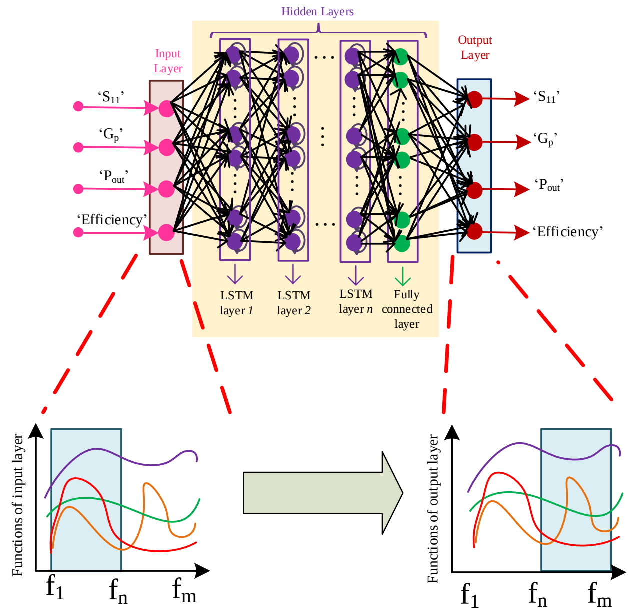

Figure 2: Proposed DNN for predicting the extended frequency of modeled PA.

Algorithm 1 Summary of proposed methodology through the LSTM-based DNN for extrapolating frequency responses of PA over the large frequency band

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1: Arrange the co-simulation environment between ADS and MATLAB;

2: Prepare dataset leading to train the DNN;

3: Achieve S_{11}, and one-tone results of PA in a large frequency band using ADS environment;

4: Construct input layer, hidden layers, and output layer of LSTM-based DNN following by the fully connected Layer;

5: Apply the rule of thumb for achieving the optimal hyper-parameters;

6: Train the network in MATLAB;

7: Predict the future performances of PA through *'predictAndUpdateState'* in MATLAB.

III. Practical Implementation of DNN

The DNN implementation is executed in Intel Core i7-4790 CPU @ 3.60 GHz equipped with 32.0 GB RAM. For validating the proposed method, the PA presented in Fig. 3 is designed within the range frequency of 1-2.3 GHz using Rogers RO4350B substrate with ε_r=3.66 and a thickness of 0.508 mm. The presented design parameters in TLs are iterated within the range of [$\mp$5%-$\mp$25%] and the step size of $\mp$5%. In each iteration, output data in terms of S_{11}, G_p, P_{out}, and η_D are gathered. In total, 5000 multi-segment sequences are extracted and through these data, the DNN is constructed for half of the determined bandwidth. The accuracy of the trained DNN is around 0.10 where it results in precise future performance prediction.

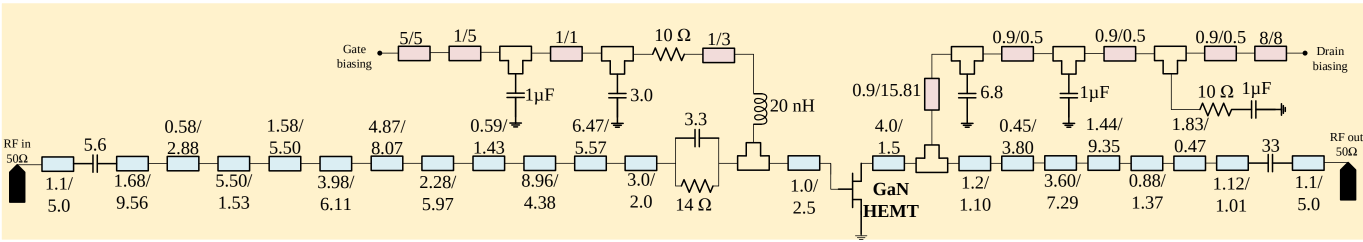

Figure 3: Designed PA for modeling through DNN; Unit of capacitors is pF and dimensions of TLs (Width/Length) are in mm unit.

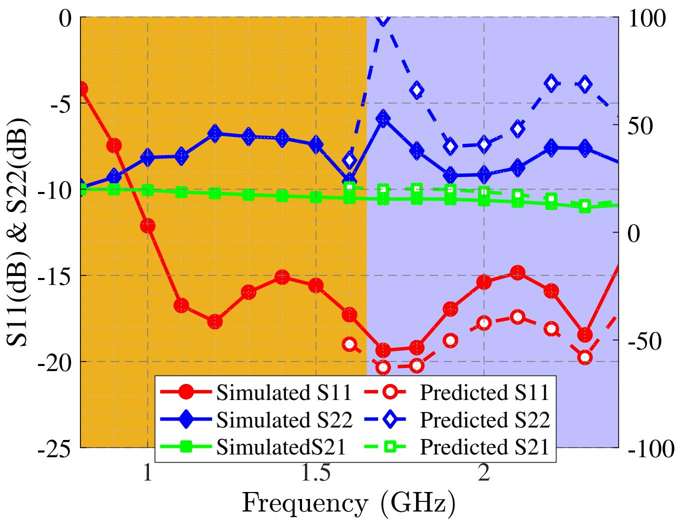

Figure 4: S parameter performances of modeled PA.

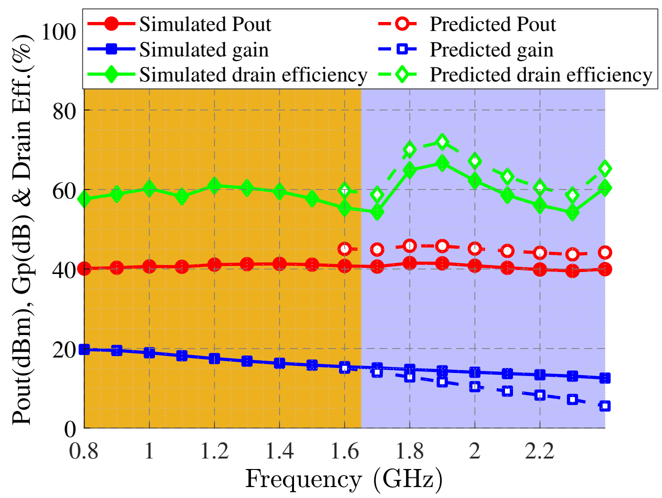

Figure 5: One-tone simulation results of PA at 3-dBm gain compression.

IV. Simulation Results

This section devotes to present the achieved various outcomes through the designed and modeled PA through LSTM-based DNN. The executed transistor model is Wolfspeed CG2H40010F Gallium Nitride (GaN) high-electron mobility transistor (HEMT) where the drain-source voltage and quiescent drain-source current are 50 V and 40 mA, respectively.

Figure 4 presents the S-parameter performances in terms of S_{11}, S_{21}, and S_{22} for the bandwidth of 1-2.3 GHz. As presented in the previous section, firstly the PA is modeled for the frequency band of 1GHz to 1.7 GHz and afterwards the trained DNN is employed results in predicting the S-parameter specifications from the 1.7 GHz to 2.3 GHz (see Fig. 4). The one-tone results depicted in Fig. 5 demonstrate that the gain G_p is higher than 15 dB and η_D is more than 55% in the operational frequency band. Additionally, the G_p with η_D specifications over the output power for various frequencies are presented in Fig. 6.

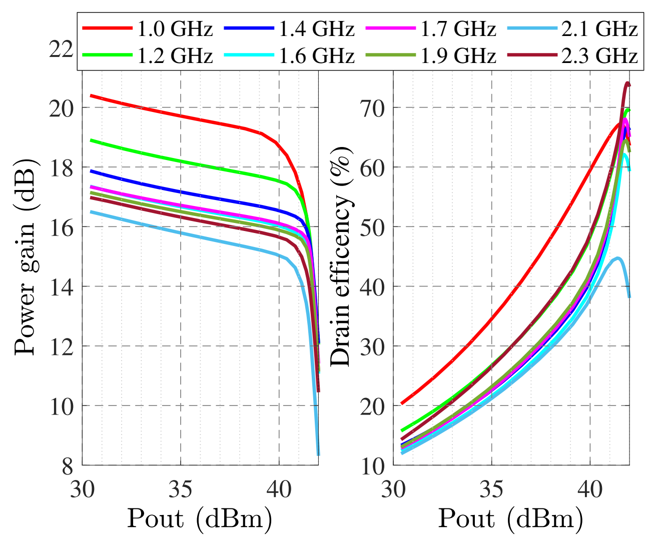

Figure 6: G_p and η_D performances through output power for various frequencies.

V. Conclusion

This paper presents an effective method in modeling the PAs through the DNN to predict the output outcomes of the PA in an extended bandwidth. The proposed approach suggests reliable PA model which reduces the designer's efforts in simulating or measuring on a large frequency band. At the first phase, the LSTM-based DNN for half of the bandwidth is trained in terms of one-tone and S-parameter results. Afterwards, the constructed DNN is employed for predicting the extended frequency responses. The validation of the proposed method is confirmed by designing a PA at 1-2.3 GHz where this methodology leads to reduce designer's effort importantly in achieving large frequency band.

The presented methodology can be regarded as a primarily demonstration of the DNN capability. The numerical advantage of this method becomes increasingly competitive with other modelling approaches once the DNN can extrapolate the model validity over even wider bandwidth with respect to the extraction frequencies. As a future work, advanced multi-objective algorithms will be employed for performing optimization in a wideband operational frequency band and to test the model validity on complex PA topology, e.g. requiring harmonic tuning in the matching networks. Furthermore, electromagnetic simulations of the passives are also extremely demanding in terms of numerical effort, hence the model advantages will be bench-marked against EM simulations.

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