

# Chapter 3

## Automated Power Amplifier Design Through Multiobjective Bottom-Up and Particle Swarm Optimizations Using Neural Network



Lida Kouhalvandi and Ladislau Matekovits

**Abstract** This study presents an automated power amplifier (PA) design process by optimizing the topology and values of design parameters, sequentially. The automated optimization environment is created with the combination of an electronic design automation tool and a numerical analyzer. As a first step, the configuration of the PA is generated using the bottom-up optimization (BUO) method, then the values of the components are optimized using the particle swarm optimization (PSO) algorithm that is employed with a shallow neural network. The PSO method is applied for optimizing PA in terms of output power, power gain, and efficiency leading to obtain optimal design parameters. The proposed optimization process is automatic and compact leading to reduce interruptions of designers during the process. In order to verify the effectiveness of the presented method, one lumped element PA including GaN HEMT transistor is designed and optimized. The optimized PA reveals higher than 45% power added efficiency with the linear gain performance between  $10 \div 14.6$  dB in the frequency band of  $1 \div 2.3$  GHz.

**Keywords** Automated · Bottom-up optimization (BUO) · Multiobjective · Particle swarm optimization (PSO) · Power amplifier · Shallow neural network (SNN)

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### 3.1 Introduction

Future mobile networks supporting the sixth generation (6G) technology require high performance systems that can manage high amount of data. For this case, power amplifiers (PAs) play an important role in the wireless communication systems [1, 2] and they must be of high performance in terms of output power ( $P_{out}$ ), power gain ( $G_p$ ), and power added efficiency (PAE) [3]. Concurrently achieving these three significant specifications is not straightforward and requires multiobjective optimization-based methods.

Optimization-based approaches, opposite to the Knowledge-based approaches, are divided into three techniques, namely: equation-based, simulation-based, and learning-based approaches [4]. In the field of radio frequency (RF), there is a large amount of data to be dealt with due to the non-linearity of active devices and harmonic effects of passive and active components. Hence, learning-based method gets the attention of researchers as this method can pave the ways of RF designs by modeling the circuits. This type of learning provides the relationships between the input and the output data that are design parameters and design specifications, respectively [5, 6] by properly weighting the available design parameters. This method has been recently applied for sizing the included design parameters (input) [7] and is employed to optimize various design specifications (output) of PAs. From another point of view, this type of learning provides an automated environment and reduces the dependency to the designer's experiences.

This work presents a two-phase optimization process that is performed automatically and sequentially aiming to both configuring the structure and also predicting the design variables. The first phase optimization is applied using the bottom-up optimization (BUO) algorithm where the lumped element input and output matching networks (MNs) are constructed. Then the multiobjective particle swarm optimization (PSO) algorithm is employed for optimizing the design parameters of the constructed PA in the first phase. This algorithm is employed using the shallow neural network (SNN) includes one hidden layer and optimizes three important specifications of PA that are output power, gain, and efficiency. As Fig. 3.1 represents, the proposed method paves the way of RF designers to reduce the human interruptions during the optimization process where by selecting the transistor model, both the structure and values of design parameters are optimized automatically.

This paper is organized as follows. Section II provides in detail descriptions about the optimization process. The validation of the method is provided in Sec. III by designing and optimizing a wideband lumped element PA. Finally, Sec. IV concludes this work.

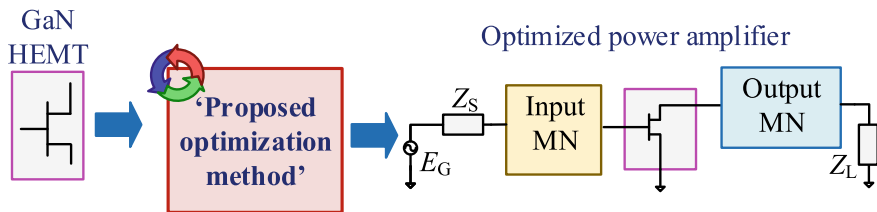


Fig. 3.1 General flowchart of proposed optimization method

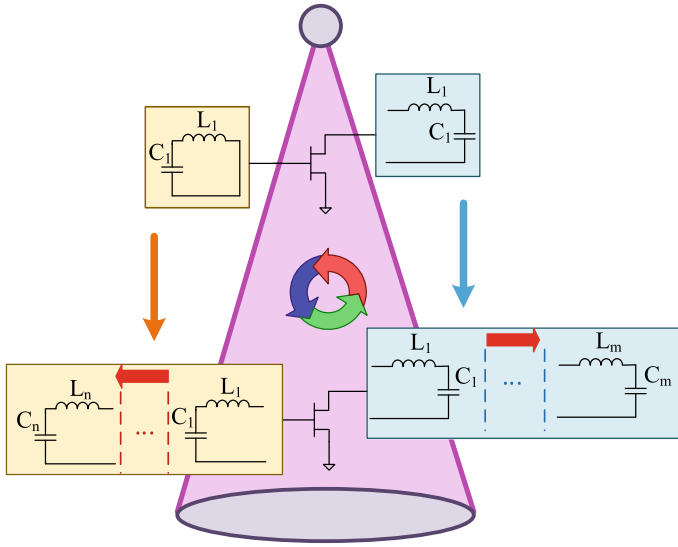
## 3.2 Proposed Automated Optimization Process

Our presented method is devoted to concurrently optimize *i*) the general structure of the PA that includes reactive components (i.e., capacitor (C) and inductor (L)), and *ii*) the optimal values of involved components. The first phase is performed by applying the BUO algorithm and the second phase is executed using the multiobjective PSO algorithm. The PSO method is employed using a shallow neural network (SNN). More importantly, the entire optimization process is performed automatically in the created environment that is the combination of electronic design automation (EDA) tool, as ADS, and numerical analyzer, as MATLAB. Interested reader in further details can refer to [8] for getting the view point of constructed optimization platform. In this section, the detailed description of an automated optimization-oriented process are given that leads to optimize the lumped element PA in terms of  $P_{out}$ ,  $G_p$ , and  $PAE$ .

### 3.2.1 Bottom-Up Optimization (BUO) Algorithm

Providing that the first structure of any PA includes input and output MNs, is an important step in RF designs. In order to obtain the optimal structure and configuration of the PA, the BUO method is employed in this paper. This method starts with one unit cell (that includes one capacitor and one inductor) in both input and output sides of MNs; sequentially increases in the number of unit cells as Fig. 3.2 shows is then performed. Regarding the depicted Smith chart in [9], inductor-capacitor networks that are normalized to  $50 \Omega$  are used as the unit blocks of MNs.

As mentioned above, the BUO starts with one unit cell in the input and output MNs and sequentially increases their number on both sides up to achieving the determined design goals. The initial values of each C and L are determined by employing the *random optimization (RO)* method presented in [8]. This optimization process leads to generate the optimal configuration of the PA that consists of passive L and C components and also provides an effective way of synthesizing the MN topologies.



**Fig. 3.2** BUO algorithm for configuring the structure of the PA design

### 3.2.2 Particle Swarm Optimization (PSO) Algorithm

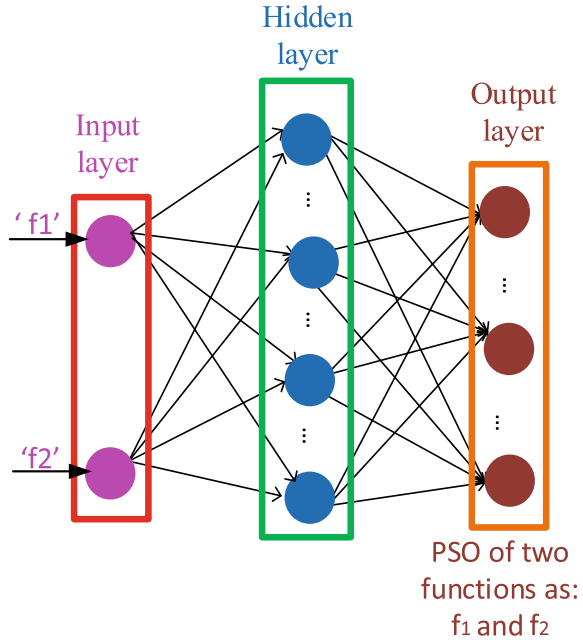
After constructing the PA's structure using the BUO algorithm, the optimal values of design parameters (i.e., Cs and Ls) must be determined. For this case, the multi-objective PSO algorithm [10] is employed for achieving the optimal variables. This algorithm is based on the Pareto Optimal Front (POF) and aims to find the optimal values achieved by trading-off between two functions namely  $f_1$  and  $f_2$ . For our problem, these two functions are represented as  $f_1 = G_p(P_{out})$  and  $f_2 = PAE(P_{out})$  where both  $G_p$  and  $PAE$  are functions of output power.

For employing this algorithm, we get benefit of learning-based approach that is using the SNN. Figure 3.3 shows the implementation of multiobjective PSO algorithm using the SNN. This network consists of one hidden layer with several neurons. For obtaining the optimal number of neurons, the *rule of thumb* approach is employed [11].

### 3.3 Designed and Optimized Lumped Element PA

For validating the proposed optimization process, one lumped element 10W PA in the operational frequency band from 1 GHz to 2.3 GHz is designed and optimized. The used transistor model is Wolfspeed CGH40010 Gallium Nitride (GaN) high-electron mobility transistor (HEMT) and the designed PA is implemented on Rogers RO4350B substrate with relative dielectric constant  $\epsilon_r = 3.66$  and a thickness of

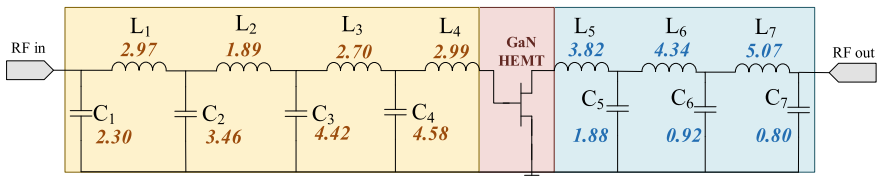
**Fig. 3.3** Employment of the multiobjective PSO algorithm through shallow neural network for predicting the optimal design parameters;  $f_1 = G_p(P_{out})$  and  $f_2 = PAE(P_{out})$



0.508 mm. The optimization process is performed on CPU execution environment that has specifications as: Intel Core i7-4790 CPU @ 3.60 GHz with 8.0 GB RAM.

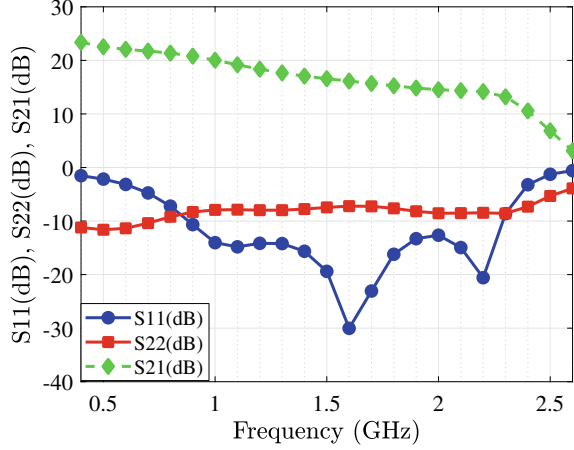
Figure 3.4 shows the optimized PA by using the BUO and PSO algorithms leading to generate optimal structure with sizes of included components. As can be seen, the BUO algorithm provides four unit cells in the input MN side and three unit cells in the output MN sides. The initial reactive component values are achieved using the RO method where the values are randomly increased or decreased.

After constructing the PA, it is time to achieve the optimal component values. For this case, suitable amount of data must be created for training SNN. Randomly the component values are changed and the corresponding PA responses (i.e.,  $P_{out}$ ,  $G_p$ , and  $PAE$ ) over the interested frequency band are achieved. In total 1000 training



**Fig. 3.4** Optimized lumped element PA using the BUO for constructing the PA structure and also the PSO method for optimizing the design parameters sequentially and automatically; The units for each inductor and capacitor are nH and pF, respectively

**Fig. 3.5** S-parameter simulation results of optimized PA in Fig. 3.4



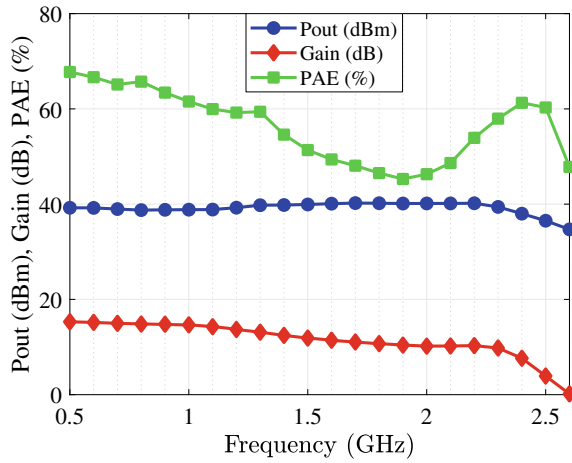
data and 500 testing data are obtained and the rule of thumb approach is applied for predicting the optimal neuron numbers. The number of neurons are achieved by using the training/testing data and also applying the rule of thumb approach where the simulation results reveal that when there are 100 neurons in the hidden layer, the training and testing accuracy are 95.54% and 93.02%, respectively.

The optimized values of passive components are shown in Fig. 3.4 and the related simulation results are presented in Figs. 3.5, 3.6, 3.7. Figure 3.5 presents the S-parameter simulation results in terms of  $S_{11}$ ,  $S_{22}$ , and  $S_{21}$ . For the optimized PA, the  $S_{11}$  is lower than -30 dB in the whole operation frequency band. The PA achieves a simulated  $S_{21}$  of 20 dB at 1 GHz and it remains flat and higher than 14 dB in the operation frequency band. The optimized three specifications (i.e.,  $P_{out}$ ,  $G_p$ ,  $PAE$ ) are shown in Fig. 3.6 that are extracted at 3-dB gain compression. The automatically optimized PA reveals around 40 dBm output power in the operation frequency band. The minimum and maximum  $PAE$  values appears at 1.9 GHz and 1 GHz that are 45.28% and 61.54%, respectively. Additionally, the stability of the optimize PA is reported in Fig. 3.7 that illustrates its well performance in the large signal operation frequency band.

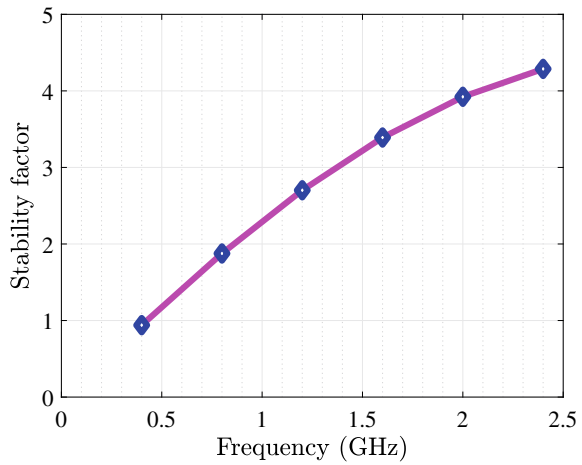
### 3.4 Conclusion

This work presents an automated optimization process for designing a lumped element PA using the BUO and PSO algorithms sequentially. Firstly, the BUO method is employed for configuring the structure of the PA. Then, the multiobjective PSO algorithm is employed with a SNN for achieving the optimal values of reactive components. The presented method is used for optimizing concurrently the output power, gain, and efficiency specifications of the PA. This learning-based optimization

**Fig. 3.6**  $P_{out}$ ,  $G_p$ , and  $PAE$  results of optimized PA @ 3-dB gain compression



**Fig. 3.7** Stability factor of optimized PA



method is performed with the combination of ADS and MATLAB which provides a fully automated platform. For validating the proposed method, one PA in the frequency band  $1 \div 2.3$  GHz is designed and optimized. The simulation results illustrate that in the operation frequency band, the achieved power gain is flat and higher than 10 dB and also the efficiency can reach maximum 61.5%.

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