Exploring Artificial Intelligence-based Optimizations for Designs Involving Active and Passive Components: Theories, Methods, Implementations, and Applications

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Abstract: The cooperative presence of active and passive devices, such as amplifiers and antennas, is well-settled in wireless communication systems. Due to the complexity of such systems, their design requires the use of advanced methodologies along with optimization methods. Recently, Artificial Intelligence (AI) has proved its effectiveness in various fields and applications, leading to the acceleration of design and optimization processes. Therefore, this paper aims to present various methodologies used in the shared design and optimization of amplifiers and antennas using the AI method in terms of optimal structure arrangement and configuration sizing. In this paper, the practical procedure for implementing AI for the design and optimization of large-scale projects is described. In short, the use of this method (i.e., AI) requires the collaboration of electronic design automation (EDA) and numerical analyzer tools, simultaneously leading to the creation of an automated environment. Readers of this study will gain an overview of AI implementation for high-dimensional projects. Depending on the need determined by the specific project, one or more of the methodologies described in this paper may be used.

Keywords: Artificial intelligence (AI), automation, antenna, neural networks (NN), optimization, power amplifier (PA).

(Title and abstract in Romanian)

Explorarea Optimizarilor Bazate pe Inteligență Artificiala pentru Proiecte care Implică Componente Active și Pasive: Teorii, Metode, Implementari și Aplicații

Abstract: Prezența cooperativă a dispozitivelor active și pasive, cum ar fi amplificatoarele și antenele, este bine stabilită în sistemele de comunicații fără fir. Datorită complexității acestor sisteme, proiectarea lor necesită utilizarea unor metodologii avansate împreună cu metode de optimizare. Recent, Inteligența Artificială (IA) și-a dovedit eficacitatea în diverse domenii și aplicații, conducând la accelerarea proceselor de proiectare și optimizare. Prin urmare, această lucrare își propune să prezinte diverse metodologii utilizate în proiectarea și optimizarea comună a amplificatoarelor și antenelor folosind metoda IA, în ceea ce privește aranjamentul optim al structurii și dimensionarea configurației. În această lucrare, este descrisă procedura practică pentru implementarea IA în proiectarea și optimizarea proiectelor de mare anvergură. Pe scurt, utilizarea acestei metode (adică IA) necesită colaborarea dintre uneltele de automatizare a proiectării electronice (EDA) și cele de analiză numerică, conducând simultan la crearea unui mediu automatizat. Cititorii acestui studiu vor obține o imagine de ansamblu asupra implementării IA pentru proiecte de dimensiuni mari. În funcție de necesitatea determinată de proiectul specific, una sau mai multe dintre metodologiile descrise în această lucrare pot fi utilizate.

Keywords: Inteligența Artificială (IA), automatizare, antene, retea neurale (NN), optimizare, amplificator de putere.

I. INTRODUCTION

With the development of communication systems, data traffic is increasing exponentially, resulting in various new issues and drawbacks. These challenges can be formulated by considering the necessity for mobility issues [1], big system capacity [2], energy consumption [3], performance metrics [4], and so on. Hence, the implementation of powerful and suitable optimization methods will help in enhancing the overall performance of systems. Recently, the Artificial Intelligence (AI) method has proven its novelty in solving high-dimensional designs, leading to improved performance of devices in terms of targeted output specifications.

In [5], the Machine Learning (ML) method is employed for reducing the calculation time, leading to predicting the path loss model in indoor scenarios in a much faster way.

The ML method is employed in [6] for an analog radio-over-fiber link, leading to enhancing receiver sensitivity. The combination of a Reinforcement Learning (RL) algorithm and a Deep Q-Neural Network (DQN) is employed in [7] for managing congestion control under a User Datagram Protocol environment. The RL is also executed in [8] to achieve robust and low-overhead security in the reconfigurable Power Amplifier (PA) designs. The Federated Learning (FL) is another learning framework that is executed over wireless networks. In [9], the FL method is used for reducing the total energy consumption over all devices. Kee et al. in [10] present detailed information about the various types of ML techniques for channel coding and describe the importance of this method for their problem.

AI methods have also been used recently in the field and domain of PAs. In [11], a Neural Network (NN) is employed for reducing baseband intermodulation distortion, which is important for Digital Pre-Distortion (DPD). A phase-normalized recurrent neural network is employed in [12] for linearizing PAs in high-bandwidth communication systems by focusing on the memory effects. Since the DPD issue is significant in PA designs, a Deep Neural Network (DNN) is executed to minimize the computational complexity and memory footprint. In [13], the DPD issue is studied with the help of Recurrent Neural Network (RNN) for enhancing the overall performance of PA.

Alike the use of AI in the PA designs, it is also executed in the domain of passive devices as antenna designs. In [14], the NN is used for analyzing and evaluating the Specific Absorption Rate (SAR) that results in reducing test time costs. The Convolutional Neural Network (CNN) is used in [15] in the field of adaptive broadband digital beamforming for the generation of beamforming Weights. With the help of synthetic NN, in [16], a reconfigurable metasurface is presented, which solves the limit of metasurfaces' intrinsic scale.

By reviewing the up-to-date references, it is observed that *the AI and ML methods are widely used in designing and optimizing wireless systems, PAs, and antennas for various goals*. This study is devoted to presenting the use of AI in modeling and sizing the high-dimensional PA and antenna designs, leading to improving each of their overall performances. The remainder of this chapter is as follows: Section II describes the suitable generated environment for implementing AI, leading to the design and optimize active and passive devices. Section III provides a summary of some designed and optimized PAs and antennas through the AI method. Finally, Section IV concludes this paper.

II. ENVIRONMENT CREATION FOR AUTOMATED OPTIMIZATION PROCESS

The AI methods are typically implemented in interface-oriented numerical analyzer environments such as Octave, MATLAB, Python, R, etc., in which various ML libraries are included [17]. From another point of view, active and passive devices such as PA and antenna are designed in the

Electronic Design Automation (EDA) tools, software tools suitable for designing integrated circuits and printed circuit boards [18]. Some of the EDA tools are OrCAD, Cadence, Cadence Design Systems, Ansys, Keysight Technologies, SPICE simulator, etc. Hence, implementing AI methods for electronic computer-aided design requires a connection between two different environments, as numerical analyzers and EDA tools. This requires a cross-platform design; otherwise, human inference is needed. Figure 1 presents the general overview of the various environment connections between EDA tools and numerical analyzers, leading to the design and optimizing diverse active and passive devices.

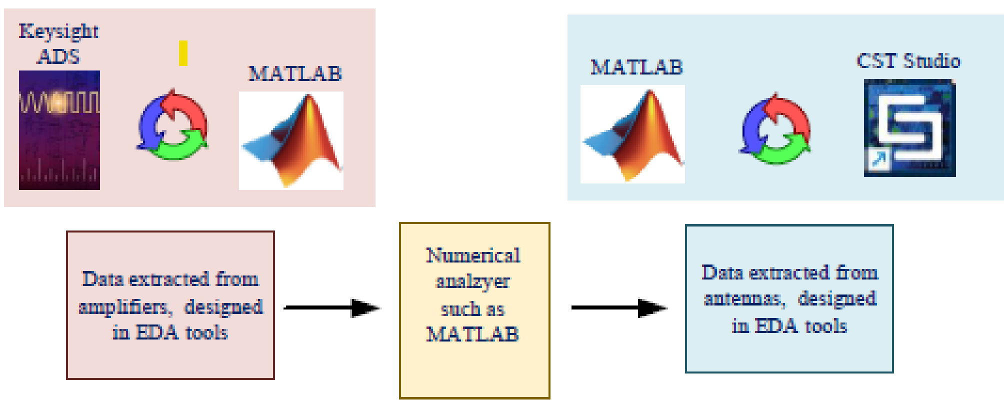

Fig. 1. Connection between EDA tools and numerical analyzers.

The main core of the presented environment is the numerical analyzer that manages all the optimization processes in which AI methods are employed. Here, the numerical analyzer is operating in the forward, and EDA tools are operating in the background prompted by the numerical analyzers [19].

III. PRACTICAL IMPLEMENTATION OF AI FOR DESIGNING AND OPTIMIZING ACTIVE AND PASSIVE CIRCUITS

After constructing an automated environment between EDA tools and numerical analyzers, the design and optimization process for PA and antenna circuits can be executed. Firstly, this section is devoted to presenting the procedures leading to constructing the initial structures of PAs and antennas. Afterward, the methodologies for obtaining the optimal design parameters are explained.

A. Generating the initial structure of PA and antenna

Configuring the initial structures of active and passive designs is not straightforward, and mostly, it depends on the designers' experience. For instance, the general structure of any PA includes input and output matching networks (MNs) with the substitution of transistor between these networks as shown in Figure 2. Hence, configuring these MNs is complex, and designers aim to construct the various networks with advanced methodologies.

To tackle this problem, there are various reported methods as below:

- Simplified Real Frequency Technique (SRFT),
- Classification DNN, • Bottom-Up Optimization (BUO),
- Top-Down Optimization (TDO).

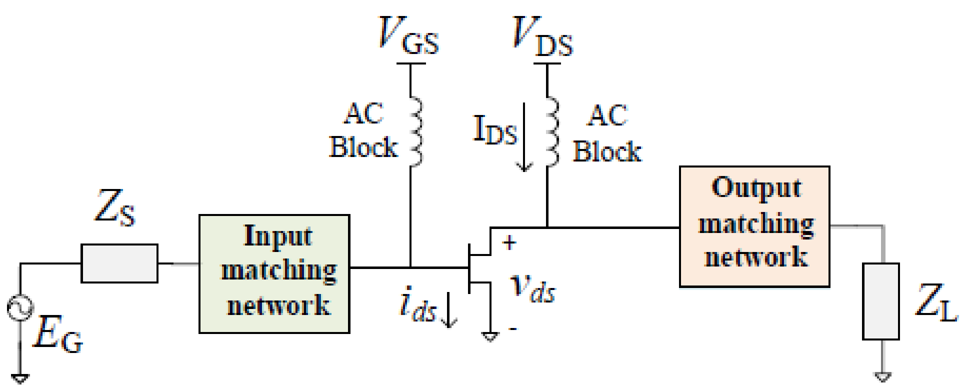

Fig. 2. General structure of any PA.

The SRFT can be a successful candidate for presenting the initial configurations for the input and output MNs by inserting the load-pull data to this method [20]. This method results in various MN typologies that vary in the number of components, including either capacitor/inductor or transmission lines (TLs). These numbers are defined by the numerator polynomial as defined in Eq. (1) in which the starting matrix (i.e., $h_0 = [\mp 1\ 0]$) has the size of $1\times m$, for all $m \geq 3$.

$$h(\lambda) = h_1\lambda^n + h_2\lambda^{(n-1)} + \ldots + h_n + 1 \qquad (1)$$

By differing the number of m in the matrix of the SRFT method, various configurations are achieved. Hence, deciding on the optimal configuration is critical. For this case, in [21], a methodology based on the classification DNN is presented, leading to the prediction of the optimal MNs based on the performance of the transistor model. Figure 3 presents the general structure of the proposed classification DNN presented in [21] in which the input specifications are phase distortion (AM/PM), amplitude distortion (AM/AM), drain efficiency (η_D), and power gain (G_p). More details regarding the construction of classification DNN are also presented in [22].

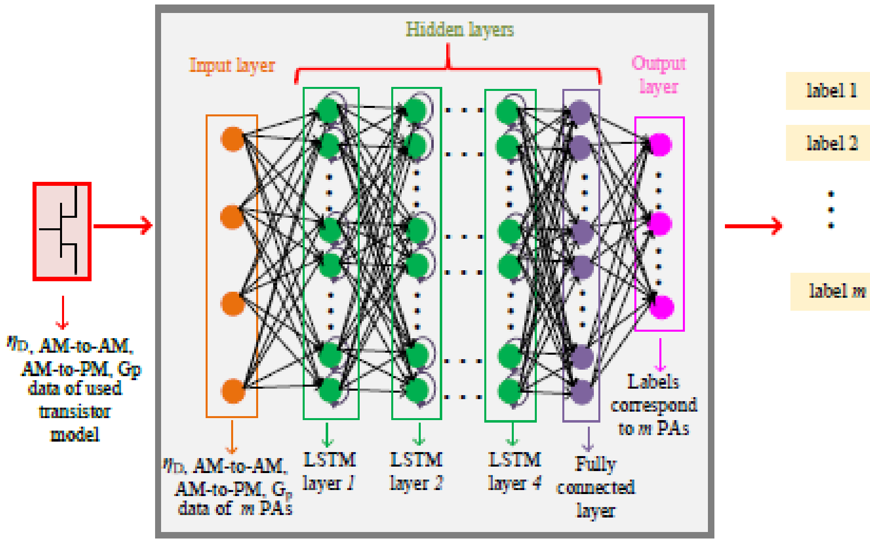

Fig. 3. Classification DNN presented in [21] for determining the optimal MNs for the PA design.

The BUO is another method leading to configuring system-level and/or circuit-level designs by decomposing into sub-blocks. This methodology starts with the lowest level and is increased sequentially and hierarchically up to achieve suitable output performance. On the other hand, the TDO method can be employed first to analyze the whole system and then break the entire system into small pieces [23]. Figure 4 presents the general flowchart of two optimizations leading to the configuration of the initial structure of active and passive designs.

The BUO and TDO methods are also employed in configuring antennas as well. Figure 5 presents the BUO method in which the optimization process starts with one TL and then is increased in the number of TLs, leading to the configuration of the antenna's structure. An example of demonstrating the TDO method is presented in [24]. Opposite to the BUO method, the TDO method is used to configure the structure of biomedical Multiple Input Multiple Output (MIMO) antenna in which firstly the biomedical layers are constructed and afterward the whole shape of the MIMO antenna is configured. Finally, the small parts of the MIMO structure are settled down (See Figure 6).

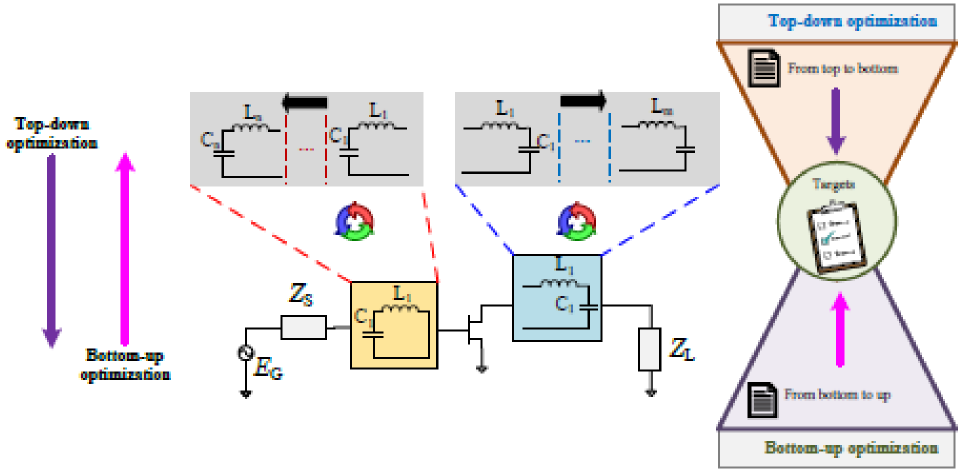

Fig. 4. A general view of process performance of BUO and TDO methods for designing a PA [19].

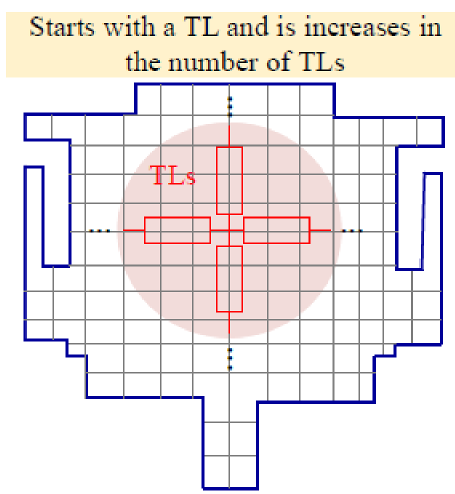

Fig. 5. Process of BUO in configuring the antenna structure.

B. Sizing of design parameters included in the configuration

The NN is a flexible structure for which the input layer and output layers can be defined by the designer. Hence in various recently published papers, AI methods are employed for sizing the design parameters of active and passive devices. Figure 7 shows the general structure of DNN where Long Short-Term Memory (LSTM) layers are used. By training accurate DNN, the determined specifications at the output layer are predicted for any given specifications in the input layer.

In [22], three specifications of PA in terms of P_{out}, G_p, and efficiency are optimized concurrently by implementing the Thompson Sampling Efficient Multiobjective Optimization (TSEMO) to the output layer of proposed LSTM-based DNN. This method (i.e., NN) can also be used in sizing the design parameters of the antenna. In [25], one-layer NN is employed for sizing the antenna for which the input layer presents the design parameters such as width and length of the antenna and output layer predicts the gain of the antenna.

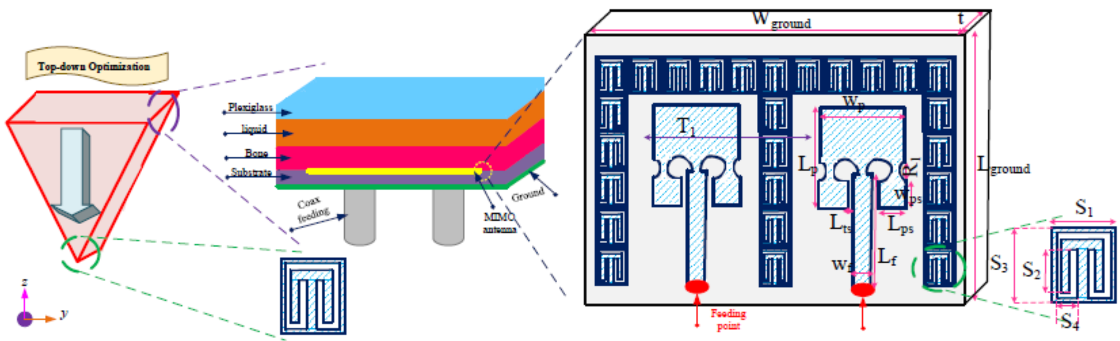

Fig. 6. TDO method for constructing the implanted MIMO antenna (width and length are in mm unit) [24].

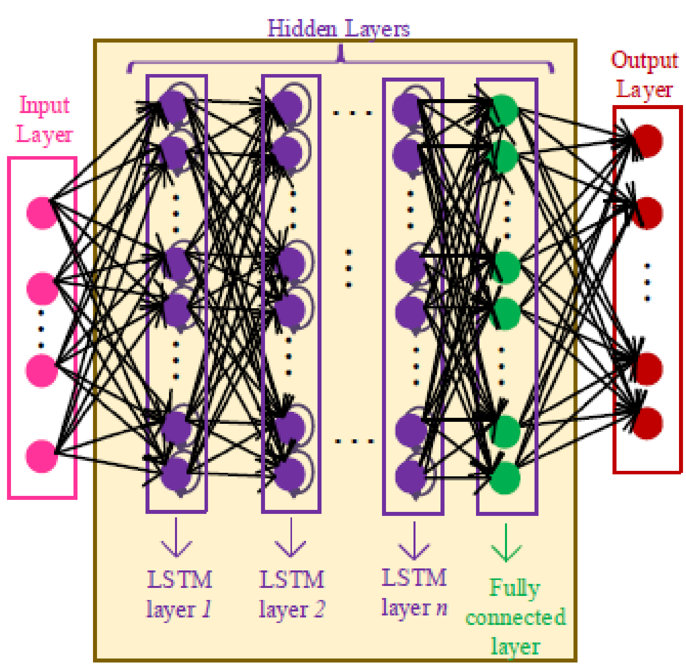

Fig. 7. General structure of DNN with LSTM layers [19].

IV. CONCLUSION

Designing and optimizing amplifiers as active devices, and antennas as passive devices are not straightforward; additional efforts are required. The AI methods prove their effectiveness in designing high-dimensional designs leading to present high-performance devices. For this case, this paper is devoted to presenting the various AI methods applied for designing and optimizing amplifiers and antennas. Implementation of AI methods for these designs requires the collaboration of EDA tools and numerical analyzers. Hence, firstly, a suitable environment must be created. Afterward, the optimal configuration of the PA and antenna can be structured through SRFT, BUO, TDO, and/or classification neural networks. Finally, neural networks (preferably regression networks) can be trained to optimize the targeted specifications of designs and achieve the optimal design parameters. By using the AI methods, human inference is reduced, leading to fewer errors, and the time consumed for optimizing these designs is reduced.

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