Combinational of GAN and LSTM-Based DNN for Automatic Optimization of Active and Passive Devices

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***Abstract*—Future high-data-rate communication systems include concurrent utilization of active and passive devices as power amplifiers (PA) and antennae. Hence for these high dimensional designs, determining an accurate starting point along with achieving acceptable outcomes are required effectively. This paper is devoted to presenting the implementation of two types of neural networks: generative adversarial network (GAN) and long short-term memory (LSTM) deep neural networks (DNNs) for both PA and antenna devices. The benefit of implementing GAN for the PA side is to estimate the load-pull contours on the Smith chart as optimal gate and drain impedances. In addition, the GAN is employed on the antenna side to predict the radiation pattern outcomes for the determined frequency. From another point of view, the LSTM-based DNN with the utilization of the Thompson sampling efficient multi-objective optimization (TSEMO) is presented for predicting the optimal design parameters leading to achieving the targeted specifications for both active and passive devices. The presented methodology is validated by designing and optimizing a PA with a multiple-input and multiple-output (MIMO) antenna operating at an approximate bandwidth of 2.68 GHz.**

I. Introduction

The optimization is the significant means for improving the overall performances of various high-dimensional designs such as power amplifiers (PAs) as active devices and antennas as passive devices [1]–[4]. Concurrent utilization and optimization of these designs are also critical for next-generation wireless communication systems [5]. Some of the well-known optimization methods are *genetic algorithm* [6], *particle swarm optimization* [7], *artificial bee colony* [8], and *differential evolution algorithm* [9], [10]. These well-known yet conventional approaches use traditional machine learning (ML) approaches. Even though these methods are mostly used in optimizing various designs, artificial intelligence (AI)-based methods prove their effectiveness in decreasing the workload in recent years [11]–[13]. Some of the targets for implementing AI in antenna and PA designs are reported in the recently published works [14], [15].

In [16], deep learning (DL) is used for recognizing the unit failure in array antennas. The automated antenna is executed in [17] through the domain knowledge-informed reinforcement learning and imitation learning, which results in at least 50% fewer adjusting steps in comparison with conventional ones for achieving antenna design at various frequencies. In [18], with the help of a multidimensional search algorithm, an automatic PA is designed to determine the suitable compromise between fundamental and harmonic impedance terminations. In another study, [19], a DL-based downlink beamforming technique is presented, which is suitable for a distributed network with PAs and results in a higher effective sum rate. The DL method is employed in [20] for designing a pattern reconfigurable neural network leading to induce channel state information for other various radiation modes. In [21], a PA modeling with the help of DL is executed to decrease the training time. A beam selection method with the help of a convolutional neural network (CNN) is introduced in [22] that is suitable for a switched beam antenna.

As reported in [23], acceptable results can be achieved when separating the system into various designs; this paper is devoted to introducing an automated methodology that leads to designing and optimizing high-performance antennae with PA at the common bandwidth through AI-based methods. Two types of neural networks (NNs) as generative adversarial network (GAN) and long short-term memory (LSTM)-based deep neural network (DNN) with the implementation of Thompson sampling efficient multi-objective optimization (TSEMO) are used [24]. The GAN is trained on the antenna side for predicting the radiation patterns (RPs) at both the E-plane and H-plane, and it is also constructed on the PA side for forecasting the optimal gate and drain impedances through the Smith chart based on load-pull contours. Also, the LSTM-based DNNs are trained for optimizing the design parameters of PA and antenna for the determined output specifications. All the optimization process is executed automatically with the combination of the electronic design automation (EDA) tool and numerical analyzer: here, *Keysight ADS* and *CST* software are used for designing and optimizing the PA and antenna sequentially, and MATLAB is used as the numerical analyzer. By practically designing and optimizing active and passive devices, it is observed that reliable outcomes are achieved without manual interruptions.

This paper is organized as follows: Section II presents the employed methodology leading to optimizing antenna and PA through GAN and LSTM-based DNNs. Section III explains the obtained simulation results for the practical design of devices through the proposed method. Finally, Section IV concludes this paper.

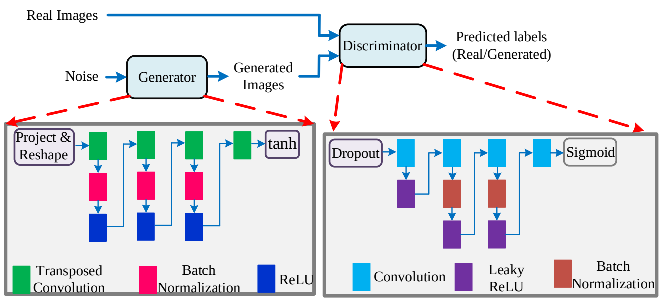

Fig. 1. Structure of GAN to be used in PA and antenna devices.

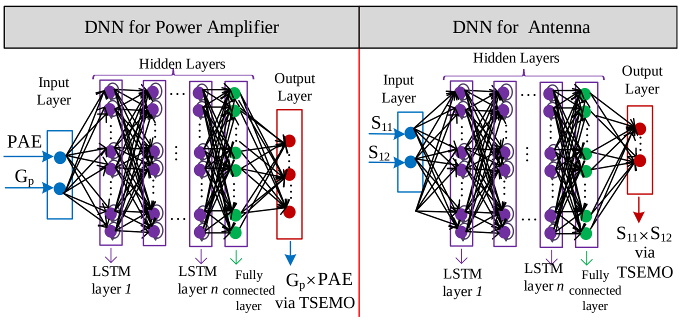

Fig. 2. Proposed LSTM-based DNNs for optimizing PA and antenna for diverse specifications.

II. Proposed Methodology

The concurrent use of PAs with antennas is important for wireless communication systems. Hence, advanced methodologies are required for designing and optimizing these high-dimensional circuits. This section is devoted to summarizing the presented method based on using two NNs: GAN and LSTM-based DNN at both design sides.

1) GAN structure: The GAN topology is a DL-based architecture that includes two DNNs—the generator network and the discriminator network, as depicted in Fig. 1. The generator section produces data with the same topology as the training data and the discriminator section leads to classifying the observations as either ‘real’ or ‘generated.’ In summary, this kind of network can produce data with similar properties as the input real data [25]. On the PA side, load-pull images are employed in which the discriminator section learns about the process of realizing valid load-pull contours. On the antenna side, the GAN is trained to forecast the RPs at a specific frequency.

2) LSTM-based DNN along with the implementation of TSEMO method: To obtain the optimal design parameters that result in acceptable outcomes, a DNN using LSTM layers and implementing the TSEMO method is constructed. In this regression task, the rectified linear unit (ReLU) function is employed as the activation function, and the loss function is the root mean squared error (RMSE). Fig. 2 presents the proposed two LSTM-based DNNs: 1) for optimizing PA in terms of power gain (G_p) and power added efficiency (PAE), and 2) for optimizing antenna in terms of S-parameters such as S_{11} and S_{12}. For the output layer of presented DNNs, the TSEMO method is employed, which is a multi-objective optimization and is based on the Bayesian optimization (BO) approach that builds Gaussian process (GP) [26]. The general definition is presented in (1):

$$\text{minimize}_{x\epsilon\chi\subseteq\mathbb{R}^d} G(x) = \left[g_1(x), g_2(x), ..., g_m(x)\right] \quad (1)$$

in which χ is the design space, x is the decision vector, and G is a vector of m objective functions ($g_i(x)$).

For multi-objective functions, this optimization algorithm gets points to approximate the Pareto optimal front (POF) of the various objective functions. As Fig. 3 shows, two functions as f_1 and f_2 are optimized concurrently, and finally, the last optimal outcome is the one that is near the Pareto set.

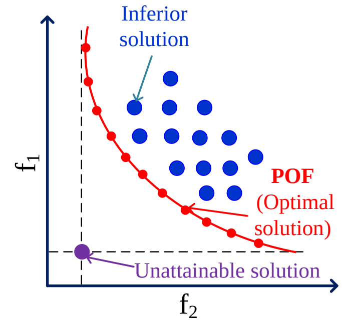

Fig. 3. Demonstration of the POF for the executed functions: f_1 and f_2 functions for PA design are PAE and G_p, and for antenna design are S_{11} and S_{12}.

III. Simulation Results

The proposed methodology is validated by designing and optimizing a multiple-input multiple-output (MIMO) antenna and PA operating at a bandwidth between 7.86 GHz and 10.54 GHz. All these automated optimization methods are executed in a practical CPU execution environment: Intel Core i7-4790 CPU @ 3.60 GHz equipped with 64.0 GB RAM. In the communication sections, the transmitter section includes the concurrent use of PA and antenna. Hence, we first design and optimize a PA, and afterward, the optimization of the MIMO antenna is completed. This section presents the simulation results achieved from designed active and passive devices.

A. Optimized PA

Fig. 4 presents the optimized PA for which, firstly, the GAN network is trained and constructed for predicting the optimal drain and gate impedances. Here, 5000 sets of randomly extracted load-pull outcomes are used for training the network in which transposed convolution layers, and convolution layers include 5-by-5 filters. Table I presents the summary of predicated impedances through the GAN network. Here, a Gallium Nitride (GaN) high-electron-mobility transistor (HEMT) is used from WIN 0.25 μm GaN process technology, and the PA is biased at a drain-source voltage of 28 V and a quiescent drain-source current of 100 mA. Here, the employed substrate is Rogers RO4350B with ε_r=3.66 and a thickness of 0.508 mm.

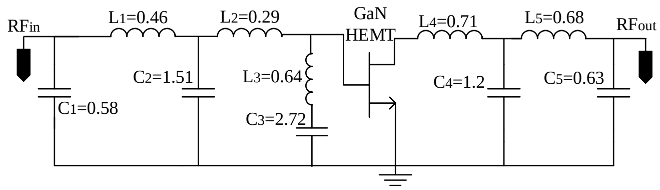

Fig. 4. Optimized PA; the units for capacitors and inductors are pF and nH, respectively.

TABLE I
PREDICTED LOAD-PULL RESULTS AT 3-DB GAIN COMPRESSION WITH GAN NETWORK.

Freq. (GHz)	**Gate Impedance**	**Drain Impedance**	**PAE (%)**	G_p **(dB)**
8	1.8-j6.7	16.4-j30.5	11.7	63.8
9	1.7-j5.8	14.8-j28.7	10.9	62.2
10	1.7-j5.0	11.9-j25.6	10.1	60.9
11	1.6-j4.4	10.5-j24.3	9.5	59.8

After achieving the optimal impedances, the initial structure of PA is generated. Afterward, the LSTM-based DNN is trained in which the input layer represents the G_p and PAE results, and the output layer presents the optimized values of the input-layer specifications through the TSEMO method (see Fig. 2). For this case, the values of inductors ('L') and capacitors ('C') are iterated randomly, and in total, 3000 data is generated. Fig. 5 shows the accuracy of the trained two neural networks. It is observed that the optimal required epoch for the GAN network is 1000, and also, the LSTM-based DNN achieves 0.078 normalized RMSE in a network with 3 hidden layers.

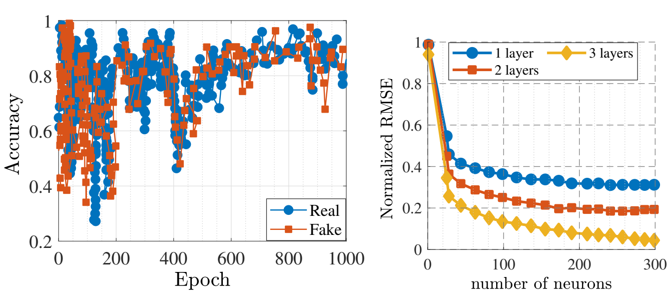

Fig. 5. Accuracy representation for GAN (left-side) and LSTM-based DNN (right-side) for the optimized PA.

B. Optimized MIMO antenna

Fig. 6 shows the optimized MIMO antenna in which the LSTM-based DNN is employed for obtaining the optimal design parameters (see Fig. 2). For this passive device, two specifications, S_{11} and S_{12}, are optimized via the TSEMO algorithm. Similar to the trained DNN in the PA section, the design parameters such as the width ('W') and length ('L') of the MIMO antenna are iterated randomly, resulting in a total of 1500 data needed for training the DNN. The MIMO antenna is implemented on the FR-4 substrate with a loss tangent of δ=1e-3 and ε_r of 4.3.

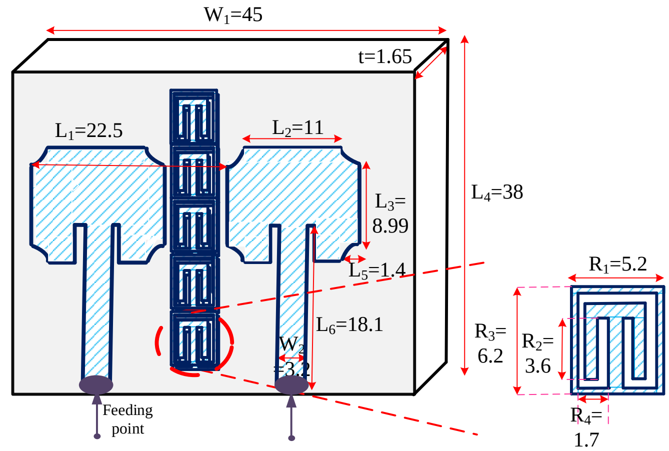

Fig. 6. Optimized MIMO antenna; all the dimensions are in mm unit.

For the antenna side, the GAN network is constructed for predicting the RPs at the E-plane and H-plane for specific frequencies. Hence, for the optimized antenna, 10000 data is generated by iterating the design parameters of the antenna randomly. Fig. 7 presents a normalized RMSE value of 0.084 at 4^{th} layer with 200 neurons for the trained LSTM-based DNN, and the acceptable accuracy for the GAN network is obtained at 1000^{th} epoch.

C. Outcomes achieved from executed methodology

For the optimized PA and MIMO antenna, determined outcomes for each one are achieved. Fig. 8 (left-side) presents the S_{11} result for the optimized PA and MIMO antenna operating between 7.86 GHz and 10.54 GHz. Also, Fig. 8 (right-side) shows two specifications of PA in terms of G_p and PAE and S_{12} performance of optimized MIMO antenna. It is demonstrated that the PAE specification is more than 50% with a linear gain of more than 10 dB at an approximate 38 dBm output power. For the MIMO antenna also, the RPs are simulated, and with GAN, the RPs at the E-plane and H-plane are predicted for 9 GHz frequency, which shows good agreement as depicted in Fig. 9.

IV. CONCLUSION

This paper presents the methodology for concurrently designing and optimizing active and passive devices with the help of NNs. The proposed method is based on the utilization of GAN along with LSTM-based DNN in which the TSEMO method is used. The GAN on the PA side is used for predicting the optimal impedances, which are the important starting points for optimizing active devices, and in the antenna it is employed for predicting the RPs at specific frequencies. Additionally, the LSTM-based DNNs at both PA and antenna sides are used for obtaining the optimal design parameters

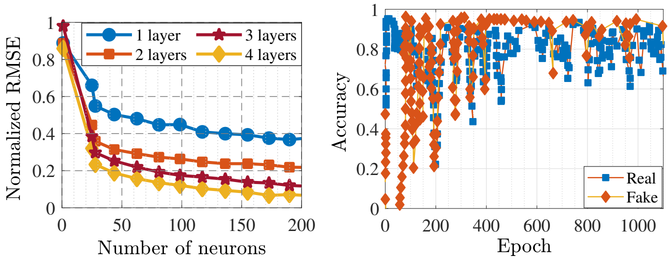

Fig. 7. Normalized RMSE value for optimized MIMO antenna (left-side) with accuracy of constructed GAN network (right-side).

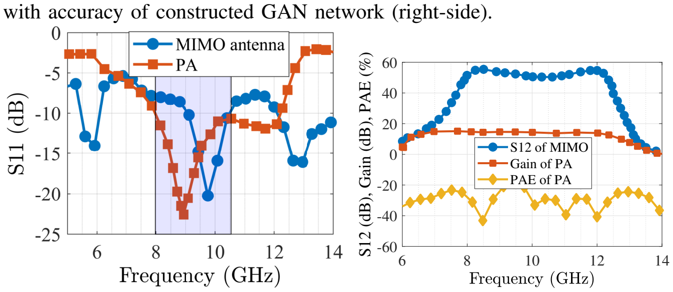

Fig. 8. Optimized S_{11} results for MIMO antenna and PA (left-side), with S_{12} results of MIMO antenna, gain and PAE results of PA (right-side).

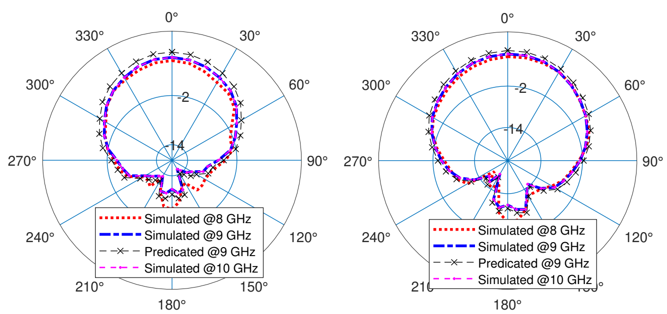

Fig. 9. RPs for optimized MIMO antenna at $\phi = 0$ (left-side), $\phi = 90°$ (right-side).

results in targeted output results. The practical effectiveness of the method is validated by optimizing the PA and MIMO antenna from 7.86 GHz to 10.54 GHz, which is executed automatically with no manual interruptions. It is observed that the proposed methodology is compact enough to find the optimal solution automatically without any need for manual post-processing.

References

[1] Y. Sun *et al.* Data-driven bayesian optimization framework for rapidly developing novel wideband, low-profile dipole antenna with 3d printed technology. *IEEE Transactions on Antennas and Propagation*, pp. 1–1, 2024.

[2] Z. Ni *et al.* Design and analysis of optimization method for ultra-wideband pa based on improved moea/d algorithm using mixed objective function. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, pp. 1–1, 2024.

[3] M. P. Yankov *et al.* Flexible raman amplifier optimization based on machine learning-aided physical stimulated raman scattering model. *Journal of Lightwave Technology*, 41(2):508–514, 2023.

[4] F. Cilici *et al.* Nonintrusive machine learning-based yield recovery and performance recentering for mm-wave power amplifiers: A two-stage class-a power amplifier case study. *IEEE Transactions on Microwave Theory and Techniques*, 72(5):3046–3064, 2024.

[5] D. Sharma *et al.* An overview for designing 6g networks: Technologies, spectrum management, enhanced air interface and ai/ml optimization. *IEEE Internet of Things Journal*, pp. 1–1, 2024.

[6] J. Pu *et al.* Notice of violation: A dual-band beam steering multi-functional reconfigurable antenna optimized by non-dominated sorting genetic algorithm (nsga-ii) for wi-fi 6 applications. *IEEE Transactions on Antennas and Propagation*, pp. 1–1, 2022.

[7] Y. Ma *et al.* Threshold optimized dvr model for rf power amplifier using particle swarm algorithm for 5g application. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, pp. 1–1, 2024.

[8] L. Wang *et al.* Antenna array design by artificial bee colony algorithm with similarity induced search method. *IEEE Transactions on Magnetics*, 55(6):1–4, 2019.

[9] T.-Y. Gao *et al.* A hybrid self-adaptive differential evolution algorithm with simplified bayesian local optimizer for efficient design of antennas. *IEEE Transactions on Antennas and Propagation*, pp. 1–1, 2024.

[10] J. Chen and H. Jiang. Optimal design of gain-flattened raman fiber amplifiers using a hybrid approach combining randomized neural networks and differential evolution algorithm. *IEEE Photonics Journal*, 10(2):1–15, 2018.

[11] D.-L. Wu *et al.* Ai deep learning optimization for compact dual-polarized high-isolation antenna using backpropagation algorithm. *IEEE Antennas and Wireless Propagation Letters*, 23(2):898–902, 2024.

[12] F. Peng and X. Chen. An antenna optimization framework based on deep reinforcement learning. *IEEE Transactions on Antennas and Propagation*, 72(10):7594–7605, 2024.

[13] A. Davoli *et al.* Machine learning and deep learning techniques for colocated mimo radars: A tutorial overview. *IEEE Access*, 9:33704–33755, 2021.

[14] L. Xue *et al.* A design methodology of mmic power amplifiers using ai-driven design techniques. In *2023 19th International Conference on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design (SMACD)*, pp. 1–4, 2023.

[15] S. K. Goudos *et al.* Design of antennas through artificial intelligence: State of the art and challenges. *IEEE Communications Magazine*, 60(12):96–102, 2022.

[16] H. M. Yao *et al.* Antenna array diagnosis using a deep learning approach. *IEEE Transactions on Antennas and Propagation*, 72(6):5396–5401, 2024.

[17] Z. Wei *et al.* Automated antenna design via domain knowledge-informed reinforcement learning and imitation learning. *IEEE Transactions on Antennas and Propagation*, 71(7):5549–5557, 2023.

[18] C. Belchior *et al.* Automatic methodology for wideband power amplifier design. *IEEE Microwave and Wireless Components Letters*, 31(8):989–992, 2021.

[19] J. Jee *et al.* Cooperative beamforming with nonlinear power amplifiers: A deep learning approach for distributed networks. *IEEE Transactions on Vehicular Technology*, 72(5):5973–5988, 2023.

[20] M. Liang and A. Li. Deep learning-based channel extrapolation for pattern reconfigurable massive mimo. *IEEE Transactions on Vehicular Technology*, 73(3):4395–4400, 2024.

[21] S. Zhang *et al.* Deep neural network behavioral modeling based on transfer learning for broadband wireless power amplifier. *IEEE Microwave and Wireless Components Letters*, 31(7):917–920, 2021.

[22] M. Jamshidi and S. H. Sedighy. Practical cnn-based beam selection for wideband single-receiver switched beam antenna. *IEEE Access*, 12:153439–153444, 2024.

[23] G. L. Barbruni *et al.* A wearable real-time system for simultaneous wireless power and data transmission to cortical visual prosthesis. *IEEE Transactions on Biomedical Circuits and Systems*, 18(3):580–591, 2024.

[24] E. Bradford *et al.* Efficient multiobjective optimization employing gaussian processes, spectral sampling and a genetic algorithm. *Journal of Global Optimization*, 71(2):407–438, Jun 2018.

[25] P. Sharma *et al.* Generative adversarial networks (gans): Introduction, taxonomy, variants, limitations, and applications. *Multimedia Tools and Applications*, 83(41):88811–88858, Dec 2024.

[26] Z. Hao *et al.* Efficient hybrid multiobjective optimization of pressure swing adsorption. *Chemical Engineering Journal*, 423:130248, 2021.