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Power Amplifier Modeling along with Hyperparameter Optimization of LSTM-based DNN through Multi-Verse Optimizer

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Abstract—This work devotes to present an intelligent-based methodology leading to model characteristics of power amplifier (PA) as well as sizing, through the deep neural network (DNN). Here, the long short-term memory (LSTM) architecture is employed not only for predicting the extended frequency responses, but also for achieving optimal hyperparameters of DNN for sizing the PA accurately. The PA is modeled in terms of scattering parameters, output power, gain, and efficiency in which nature-inspired optimization algorithms are executed for determining the optimal numbers of hidden layers with neurons of LSTM-based DNN. The proposed method leads to construct a reliable network for predicting the future specifications of any PA in a reduced effort and acceptable convergence. To verify the effectiveness of proposed method, a PA with a 600 MHz is optimized for which the simulation outcomes prove that the multi-verse optimizer is strong enough for determining optimal hyperparameters of DNN.

Index Terms—Deep neural network (DNN), forecasting, hyperparameter, long short-term memory (LSTM), modeling, multi-verse optimizer (MVO), nature-inspired optimization algorithms, power amplifier (PA), sizing.

I. INTRODUCTION

In a wireless transceiver, the power amplifier (PA) is the most power demanding design that requires to operate in a region for enhancing output power (P_{out}) as well as power gain (G_p), and efficiency [1]. Hence, improving the overall performance of PA will help in increasing data rate and device density along with decreasing latency [2], [3]. Recently, various methods based on the implementation of neural networks (NNs) are presented that are targeted to improve the specifications of PA result in enhancing the wireless signal transmission over radio cellular networks.

For constructing multistate PA behavioral model, in [4] a residual selectable modeling approach is presented leading to enhance the accuracy of the modeled PA. This model is employed for the linearization technique [5]–[7] namely as digital predistortion (DPD) [8]. In [9], a method for selecting an optimal deep neural network(DNN)-based model for the

PA is presented in which the inputs are not specified. Here, the specifications of the input layer are the in-phase and quadrature-phase (I/Q) components with envelope-dependent terms. The augmented convolutional neural network is employed in [10] for modeling the intermodulation distortion, cross-modulation distortion, as well as nonlinearities useful for DPD applications. In another study, [11], the recurrent neural network is executed leading to construct behavioral modeling of PA. The presented methodology is validated by the Doherty PA units and various linearization examples. A convolutional neural network is also employed in [12] as a behavioral modeling leading to model the nonlinearity and memory effects of the PA. Another methodology based on the DNN is presented in [13] which is effective for reducing the training time of DNN by using transfer learning and is practical for PA modeling.

From another point of view, training accurately the NN for high-dimensional devices in which the output results are nonlinear features requires advanced optimization methods [14], [15]. For this case, successful optimization methods such as genetic algorithm (GA) [16], [17], and particle swarm optimization (PSO) [18] algorithms can be considered for optimizing the hyperparameters of any NNs.

By reviewing the recently published works it can be observed that a methodology for determining the optimal hyperparameters that are important for an accurate modeling of PAs is not focused. Hence, we introduce a deep neural network (DNN) based on the long short-term memory (LSTM) architecture leading to predict the extended frequency responses in terms of S-parameters along with P_{out} , G_p , and power added efficiency (PAE). As well as modeling PA through the NN, hyperparameters of network in terms of number of hidden layers and neurons are also optimized through nature-inspired optimization algorithms such as GA, PSO, artificial bee colony (ABC), ant colony optimization (ACO), and multi-verse Optimizer (MVO) [19]. For verifying the effectiveness of

our proposed method, we design and optimize a PA operating from 1.7 GHz to 2.3 GHz in which various optimization methods are employed for modeling this high-dimensional circuit through LSTM-based DNN. With the help of trained DNN, future performance prediction over the frequency is executed for S-parameters and also one-tone results which shows a great agreement with simulation outcomes. Hence, the proposed methodology will minimize the designer's effort in simulating large frequency band effectively results in reduced consumption time.

The paper is organized as follows: Section II explains the proposed methodology based on the implementation of DNN. Section III devotes to present the achieved simulation results around the optimized PA. Finally, Sec. IV concludes this study.

II. PROPOSED METHODOLOGY IN A NUTSHELL

As discussed before, recently the implementation of intelligent-based methods as NNs becomes popular since it can be a solution for nonlinearity characteristics. For these NNs, determining the optimal hyperparameters is not straightforward. Hence, advanced methodologies are required for determining these parameters effectively leading to train NNs more accurately. For this case, this section devotes to present a methodology in which the PA is modeled accurately as well as predicting the behaviour of the amplifier in frequency band in terms of output specifications.

As a first step (Step-1), it is critical to select the appropriate high-electron-mobility transistor (HEMT) results in high-performance outcomes. Afterwards, gain and drain impedances of the chosen transistor can be obtained through the load-pull simulation (Step-2). With the extracted impedances and the utilization of the simplified real frequency technique (SRFT) [20] and also bottom-up-optimization (BUO) [21], the input and output matching networks (MNs) are generated (Step-3). After generating the general topology of PA (here includes capacitor ('C') and inductor ('L') ladders), it is time for obtaining the optimal design parameters results in high performance specifications. For this case, the NN structure presented in Fig. 1 is proposed. The input specifications are the design parameters targeted to be employed for designing the PA: Here these parameters are values 'C' and 'L' executed at input and output MNs of PA. The specifications for the output layer of NN are: S-parameters (i.e., S_{11} , S_{12} , S_{22}) and also P_{out} , G_p , and PAE results. In the presented NN, the LSTM architecture is employed since it is able to handling long sequences [22]. For this case in the design and optimization of high performance PA, the LSTM layers are employed for predicting frequency-dependent output layer features in the determined bandwidth. As it is obvious, any NN can be trained in case of having suitable amount of data. This amount of data is obtained by iterating the values of LC ladders randomly within the diverse ranges of $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$. In summary, the data set includes component values $\sum_i S_{11}, S_{12}, S_{22}, P_{out}, G_p, PAE$ where i denotes to the number of iterations (Step-4). After achieving the dataset includes training and testing data, it is time to train the

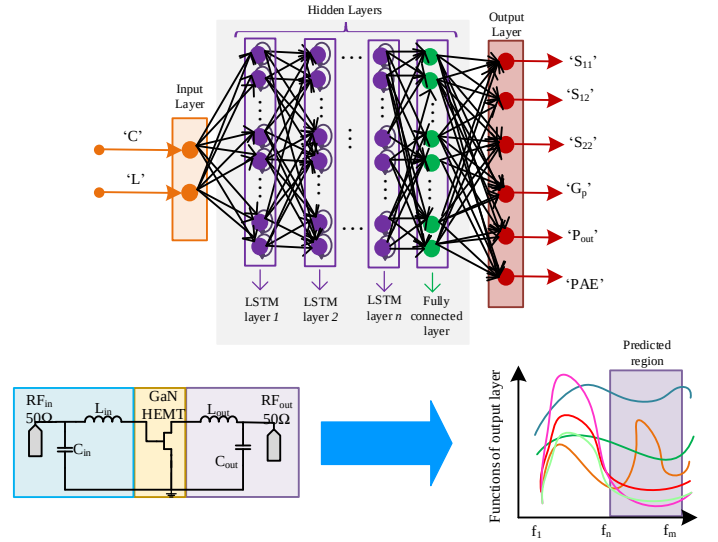


Fig. 1. Proposed method for modeling the PA by forecasting the future frequency band, along with hyperparameter optimization of LSTM-based DNN.

network along with optimizing the hyperparameters. For this case, nature-inspired optimization algorithms as GA, PSO, ABC, ACO, and MVO are employed leading to obtain optimal number of hidden layers and number of neurons in each layer (Step-5).

In our proposed network, the normalized root mean square error (RMSE) is executed as a factor for determining the convergence of network and also the rectified linear unit (ReLU) function is used as the activation function. The proposed methodology results in predicting the future output specifications of optimized PA effectively in which the network is trained with optimal hyperparameters.

III. SIMULATION RESULTS

The proposed method is validated by designing and optimizing a PA in which 'Ampleon CLF1G0060-10' as a Gallium Nitride (GaN) HEMT is used and it is targeted to obtain a 600 MHz bandwidth. The CPU execution environment for running the presented method is an Intel Core i7-4790 CPU @ 3.60 GHz equipped with 32.0 GB RAM. In this work, a 'Keysight ADS' is used as the electronic design automation tool and 'MATLAB' is executed as the numerical analyzer leading to create an automated environment and helps in training the NN. This section is devoted to present the various simulation results achieved from the proposed methodology.

After obtaining the nominated impedances through the load-pull simulation in 'Keysight ADS', the SRFT as well as BUO methods are employed for constructing the structure of PA with the initial component values. As Fig. 2 shows, the input MN includes 4-LC ladders and output MN involves 2-LC ladders. The initial values of capacitors and inductors (achieved through SRFT method) are iterated randomly results in obtaining 1100 sequences include multi-segment S_{11} , S_{12} , S_{22} , P_{out} , G_p , and PAE over the operation bandwidth. Afterwards,

the NN is prepared for being trained by arranging solver to 'adam' and 'gradient threshold' to 1 as well. Figure 2 presents the optimized PA in which the values of capacitors with inductors are obtained through the trained LSTM-based DNN as following in which the drain-source voltage with quiescent drain-source current are 50 V and 40 mA, respectively. The executed substrate is Rogers RO4350B substrate with $\epsilon_r=3.66$ and a thickness of 0.508 mm.

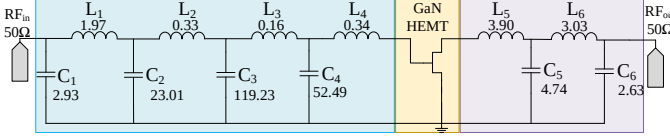


Fig. 2. Optimized PA with the proposed methodology; Unit of each capacitor and inductor are (pF) and (nH), respectively.

Figure 3 presents the normalized RMSE value over the number of neurons for various number of hidden layers. With the help of achieved dataset and also by implementing the nature-inspired optimization algorithms, it is observed that an accurate DNN is trained with a 3 LSTM layers and 300 neurons. For this case, various optimization methods as GA, PSO, ABC, ACO, and MVO are employed for determining the strong optimization method leading to accurately training the NN. As Fig. 4 presents, the MVO is the winner of this algorithm with 0.48 RMSE value which is lower and most accurate in comparison with other algorithms. By considering the two achieved results from Fig. 3 and Fig. 4, it is observed that by the implementation of MVO and increasing the number of hidden layers, a normalized RMSE value as 0.0358 is obtained for the trained PA presented in Fig. 2.

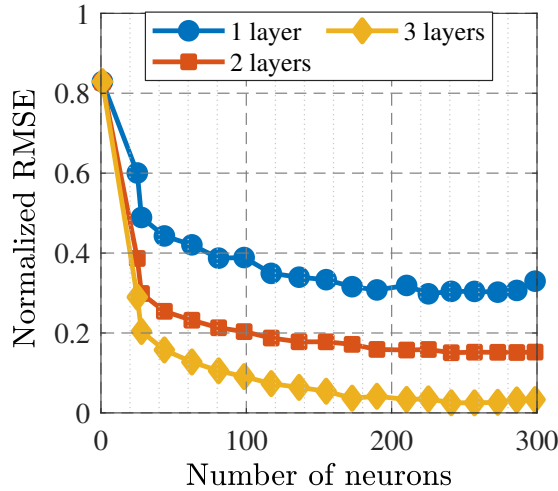


Fig. 3. Accuracy of the trained DNN through MVO algorithm with different number of hidden layers

By training an accurate LSTM-based DNN for the optimized PA, S-parameter results in terms of S_{11} , S_{22} , and S_{21} are presented in Fig. 5. For demonstrating the effectiveness of our proposed method, the simulated S-parameters are compared with the predicted outcomes through DNN from 2.1 to

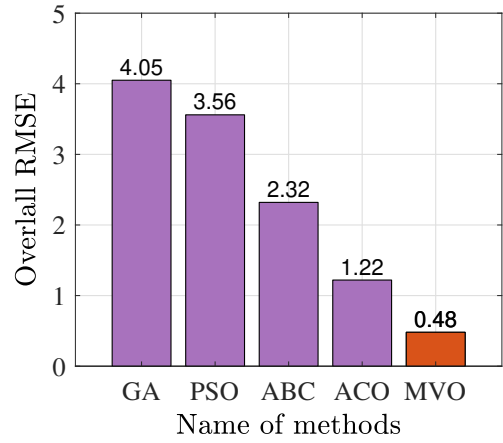


Fig. 4. Normalized RMSE over the various algorithms for determining the optimal hyperparameters of proposed NN.

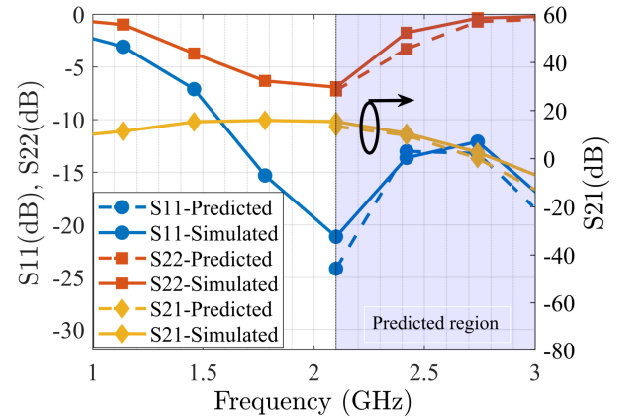


Fig. 5. S-parameter performances of the optimized PA obtained through simulations and proposed DNN.

3 GHz. It is observed that the DNN is forecasting the future performance of the PA in an acceptable and suitable manner and tracking the results achieved from simulation results. Also, three other specifications as P_{out} , G_p , and PAE at 3-dB gain compression are also simulated and predicted by the trained LSTM-based DNN. Figure 6 demonstrates that alike the presented status in the S-parameter simulation results, the predicted results are tracking the outcomes achieved through the simulated results. It is observed that the maximum PAE value around the bandwidth is 60.2% with a linear G_p value larger than 11 dB at 40 dBm output power.

IV. CONCLUSIONS

This paper presents an impressive methodology for obtaining the optimal hyperparameters of the DNN leading to accurately modeling the high-dimensional PA along with sizing the design parameters. Here the LSTM structure is employed for training the DNN, results in predicting the extended frequency responses accurately. This network can be constructed properly in case of determining optimal hyperparameters of DNN by employing four different optimizations as GA, PSO, ABC, ACO, and MVO. It is observed that the MVO algorithm is the successful one in accurately modeling the PA in terms of the

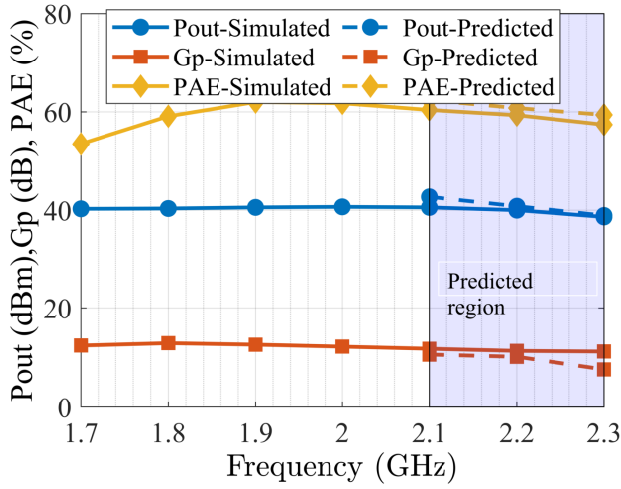


Fig. 6. P_{out} , G_p , and PAE results at 3-dB gain compression achieved through simulations and proposed DNN.

S-parameters, output power, gain, and efficiency specifications with minimum error. The presented method is flexible enough to solve the heavy reliance to the designer experience in microwave designs.

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