# Design and Modeling of RF Power Amplifiers with Radial Basis Function Artificial Neural Networks

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Abstract—A radial basis function (RBF) artificial neural network model for a designed high efficiency radio frequency class-F power amplifier (PA) is presented in this paper. The presented amplifier is designed at 1.8 GHz operating frequency with 12 dB of gain and 36 dBm of 1dB output compression point. The obtained power added efficiency (PAE) for the presented PA is 76% under 26 dBm input power. The proposed RBF model uses input and DC power of the PA as inputs variables and considers output power as the output variable. The presented RBF network models the designed class-F PA as a block, which could be applied in circuit design. The presented model could be used to model any RF power amplifier. The obtained results show a good agreement between real data and predicted values by RBF model. The results clearly show that the presented RBF network is more precise than multilayer perceptron (MLP) model. According to the results, better than 84% and 92% improvement is achieved in MAE and RMSE, respectively.

Keywords—Amplifier model; artificial neural network (ANN); class-F amplifier; radial basis function; RF amplifier

## I. INTRODUCTION

PAs are important elements, in any communication system, which consume a lot of power. Therefore, the efficiency is a very important factor in the design process. Considerable energy can be saved, by improving the efficiency of PAs [1-2]. The switching mode amplifiers are introduced to achieve high efficiency. Class-F PAs have become very popular in switching mode amplifiers, because of their high efficiency and output capability [3-5]. In the class-F PAs, Ideal drain efficiency could be obtained, due to the optimum drain voltage and drain current waveforms shape. Several methods have been introduced to model power amplifiers, such as Wiener [6] and Volterra series [7]. However, these mentioned models need approximation for obtaining the specifications of the device. Neural network based models are faster and more precise, compared with the mentioned modeling methods [8]. Any continuous nonlinear function could be approximated using ANNs. Therefore, ANNs can be used to model nonlinear circuits [9].

Power amplifiers are recently modeled, using artificial neural networks algorithms [10-12]. In [10], adaptive neuro-fuzzy inference system (ANFIS) is presented to model a PA. In this model, memory effect of the amplifier is not considered; however, the presented structure of the ANFIS is complicated. An ANN is used in [11] to model a 3G power amplifier. A large number of neurons are applied in this ANN, which makes the model complex. In this approach, the power spectral

density (PSD) is obtained, however the other specifications of the power amplifier are not considered. Neural networks have also been used to model the other microwave components [12-15]. In [12] a lowpass microstrip filter is modeled using multilayer perceptron (MLP) neural network with two hidden layers. The presented model in this research is used to predict the specifications of a lowpass microstrip filter; however, the applied model in this work is complex and uses a large number of neurons. A low voltage microwave LNA with operating frequency of 2.45 GHz is modeled in [13]. In this approach MLP, RBF and ANFIS models are investigated and the small signal parameters are considered as the input of the networks. Channel dimensions of the transistors are considered as the output of the networks. However, the presented model can only be used in the applied circuit. In [16] a microstrip patch antenna is modeled and designed using RBF network. The results in this approach show that RBF network model is more accurate than the MLP network.

An efficient class-F amplifier is modeled by neural networks in [15]. The presented ANN model in this paper can predict the efficiency and output power of the amplifier. The MLP neural network training method for ANN is used in this research. The reported errors are acceptable, but it can be improved using other ANN methods.

Recently, the RBF networks have been used to model several microwave devices [17-18]. However they have not been applied to model power amplifiers in the way, which is used in this paper.

In this paper, at first a class-F switching amplifier is designed and simulated. Then, an RBF network is proposed to model the designed amplifier precisely. Finally, the presented model is compared with the conventional MLP ANN, which shows better performances. The presented model can be used as a sub-circuit model to describe the class-F power amplifier applications. For instance, it can be used in linearization method or Doherty power amplifier structures.

## II. DESIGN OF POWER AMPLIFIER

Figure 1 shows the basic structure of the presented class-F PA, including a transistor, input/output matching network and DC supply voltage. The output matching network includes a parallel resonator circuit and a quarter wavelength transmission line [19]. The output network shapes the drain voltage and current waveforms to improve the efficiency [20]. Therefore, the output becomes short circuit in even harmonics, while it

becomes open circuit in odd harmonics. The process of drain waveforms shaping improves the efficiency of class-F PA. There are one or more odd harmonics in voltage of the drain, such that it becomes approximately a square wave. In the contrary, even harmonics in the current of the drain make approximately a half sinusoidal waveform.

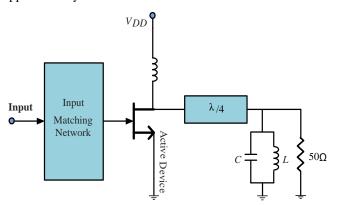


Fig. 1. Fundamental structure of the class-F PA

The designed matching circuit for the presented amplifier is shown in Fig. 2. According to this figure the applied microstrip transmission lines are shown as T1-T10, which are used as harmonic control circuits. The power relations and the power added efficiency for the presented amplifier could be given as

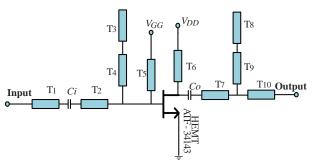


Fig. 2. Structure and matching networks of the designed amplifier

$$PAE = \frac{P_{output} - P_{input}}{P_{DC}} \tag{1}$$

$$P_{DC} = V_{DC} I_{DC} \tag{2}$$

$$P_{output} = \frac{V_m^2}{2R}.$$
 (3)

In above equations  $P_{output}$  and  $P_{DC}$  are output power and DC power, while  $P_{input}$  is the input signal power. PAs convert the DC power and power of the input signal into output AC power. According to Fig. 2, an ATF 34143 HEMT is applied in the designed PA circuit. Simulation is carried out by advanced design system (ADS) software, which contains the device model. According to simulation results, P1dB of 36 dBm is obtained. Also, the power gain and maximum PAE are 12 dBm and 76% under the 26 dBm input power. In the next section,

MLP and RBF networks will be introduced. Then, an RBF neural network model will be applied to the designed amplifier. The input and DC power of the power amplifier are assumed as input variables for the RBF network, while the output power is assumed as the output variable for the RBF network.

### III. MLP AND RBF MODELS

ANN can be considered as a mathematical system consisting of simple processing elements called neurons. These neurons can be aligned in one or multiple layers. The MLP and RBF networks are the common architectures in neural networks. The MLP feed forward network has three layers, which the first and the second are the input layer and the hidden layer. The third layer is the output layer. There are several neurons in each layer of the network and the connections between them are weighted connections. The values of weights in each layer are obtained using training algorithm, which is commonly back propagation algorithm. Applying more neurons or more layers to the network may increase the precision of the model, but it cost complexity of the network and subsequently more time is needed to simulate the presented model.

The RBF network, introduced in 1988, is a feed forward ANN. The RBF network is an artificial neural network with radial basis activation functions, including three layers in the structure. The layers of the RBF network are similar to MLP network, but there is one hidden layer in the RBF network. Source nodes are in the input layer, and there are several neurons in the second layer (hidden layer), which are called the RBF centers. The outputs of the hidden neurons are summed, by the neurons in the output layer. Activation function of the units in the second layer is radial basis function. The structure of the typical RBF ANN is illustrated in Fig. 3, including two inputs and three layers. Input layer includes input nodes with the same number as the number of input vector [21]. The *i*<sup>th</sup> neuron output in the hidden layer could be given as

$$q_i = \exp\left(-\frac{\left\|X_i - C_i\right\|^2}{\sigma_i^2}\right),\tag{4}$$

where X is input vector, C is basis function center and  $\sigma_i$  is spread of Gaussian function. The estimated output can be written as 0

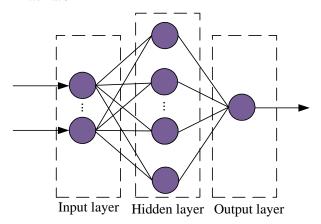
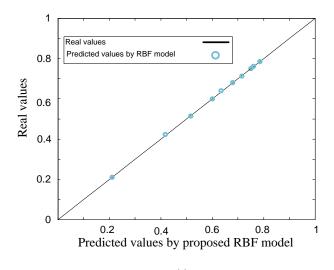


Fig. 3. Structure of the RBF ANN



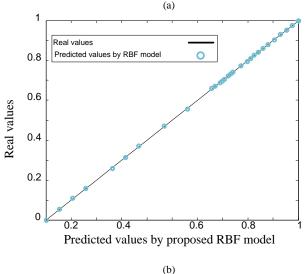


Fig. 4. Real and predicted output power results of (a) testing data and (b) training data, using RBF model

$$y = \sum_{i=1}^{n} w_i q_i \tag{5}$$

The connecting weights are shown with  $w_i$  in equation (5). The input power and DC power are assumed as input variables of the network, while, the output power is assumed as the output variable of the network. About 75 percent of data set is used for training, while 25 percent is used for testing process of the proposed model in RBF network. Detailed results of the RBF network are given in Table 1. The mean absolute error (MAE) and also the root mean square error (RMSE) for the presented network are given as

$$MAE\% = 100 \times \frac{1}{N} \sum_{i=1}^{N} |Y_{Ri} - Y_{Pi}|$$
 (6)

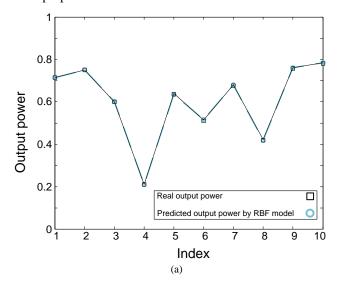
$$MAE \% = 100 \times \frac{1}{N} \sum_{i=1}^{N} |Y_{Ri} - Y_{Pi}|$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Y_{Ri} - Y_{Pi})^{2}}{N}}$$
(6)

where N is data number. The parameters  $Y_{Ri}$  and  $Y_{Pi}$ represent the real and predicted output of the presented ANN, respectively. A comparison between real and predicted output power results of training and testing data for the RBF network is illustrated in Fig. 4. Obtained errors of the presented RBF model, compared to the MLP model are summarized in Table 1. The MAE and the RMSE errors of the RBF network could be achieved using equations (6) and (7), respectively.

Real and predicted output power of the PA versus index number of each input for testing and training data using RBF network are illustrated in Fig. 5. According to Figs. 4 and 5, the predicted output power by RBF model is close to the real results. These results verify the accurate applicability of RBF network as a reliable model to predict the output power, using the input and DC power.

Real and predicted output power versus input power for training and testing data are depicted in Fig. 6. As shown in the figure, the presented amplifier is modeled precisely using the proposed RBF network. The real and predicted PAE versus input power for training and testing data are depicted in Fig. 7. Only data in the operating range of the presented amplifier are illustrated in Figs. 6 and 7. As shown, the main specifications of the designed amplifier are predicted using the presented model. Test and train data of the proposed RBF network are given in Table 2 and Table 3, respectively. Input power and DC power, which are the inputs of the network are shown in the first and second columns, while real output power and network predicted out power are compared in third and fourth columns. The predicted data have negligible deference with the real data, which verifies the presented model. 39 samples are selected for the network, which about 75% of the samples are considered for training and 25% are chosen for testing process of the proposed RBF network.



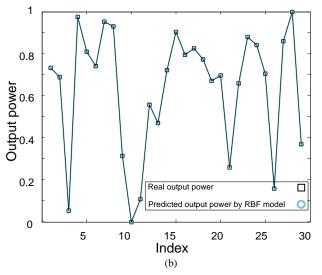


Fig. 5. Real and predicted output power of the PA versus index number of each input for (a) testing data and (b) training data, using RBF model

TABLE I. THE OBTAINED ERRORS OF THE PROPOSED RBF NETWORK

Error	Train data	Test data	Test data
	RBF	RBF	ANN[15]
RMSE	0.001	0.002	0.0275
MAE%	0.131	0.311	1.9882

TABLE II. TEST DATA OF THE PROPOSED RBF NETWORK

	Input	DC Power	Output	Network
	Power	[dBm]	Power [dBm]	Output
	[dBm]			[dBm]
1	30.0000	37.2200	36.6700	36.6764
2	33.9967	37.4800	37.2400	37.2372
3	21.9866	36.3500	34.9000	34.8896
4	13.9967	34.0700	28.8400	28.8136
5	22.9885	36.6300	35.4400	35.4966
6	20.0000	35.7700	33.5900	33.5471
7	25.9988	36.9400	36.1400	36.1266
8	17.9934	35.1900	32.0700	32.1251
9	34.9969	37.5500	37.4000	37.4027
10	36.9984	37.6900	37.7700	37.7695

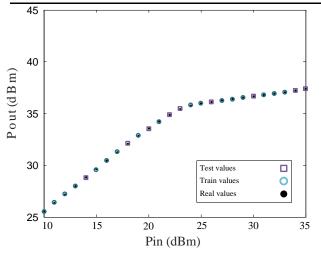


Fig. 6. Real and predicted output power versus input power for training and testing data

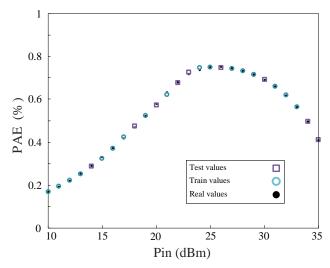


Fig. 7. Real and predicted PAE versus input power for training and testing

#### IV. CONCLUSION

An RBF network is proposed to model a linear class-F PA. Input power, DC power and output power of the PA are assumed as input and output variables of the RBF model. The RBF model results are compared with the MLP model. Normalization process is performed on the data set to enhance the accuracy of the presented model. The MAE and RMSE of 0.311 and 0.002 for the RBF network are obtained, respectively. Better than 84% and 92% improvements in MAE% and RMSE have been achieved, so, the proposed RBF network is more accurate than the MLP model. According to the reliability of the presented model, it can be used to model the designed PA as a block or a sub circuit for circuit design. The same procedure can be performed on the other RF and microwave components to achieve their artificial neural network model. Modeling of the other microwave components and amplifiers using the presented procedure will be addressed in the future work.

TABLE III. TRAIN DATA OF THE PROPOSED RBF NETWORK

	Input Power	DC Power [dBm]	Output Power	Network Output
	[dBm]		[dBm]	[dBm]
1	31.9866	37.3500	36.9400	36.9439
2	26.9984	37.0100	36.2800	36.2652
3	10.9691	33.4000	26.3800	26.4053
4	46.9984	38.9500	40.7300	40.7333
5	38.9982	37.7600	38.1600	38.1523
6	32.9885	37.4100	37.0800	37.0805
7	45.9988	38.7400	40.3900	40.3777
8	44.9969	38.5800	40.0100	40.0356
9	15.9988	34.5800	30.4600	30.4481
10	10.0000	33.1600	25.5700	25.5395
11	11.9866	33.6300	27.2000	27.2480
12	20.9691	36.0500	34.2700	34.2050
13	18.9982	35.4900	32.8500	32.8733
14	30.9691	37.2800	36.8000	36.8003
15	43.9967	38.4400	39.6300	39.6099
16	37.9934	37.6900	37.9600	37.9284
17	40.0000	37.8800	38.3900	38.4088
18	35.9988	37.6200	37.5800	37.5798
19	24.9969	36.8700	35.9800	35.9862
20	27.9934	37.0800	36.4100	36.4024

21	14.9969	34.3000	29.6500	29.5788
22	23.9967	36.7900	35.7700	35.8245
23	42.9885	38.2900	39.2400	39.2297
24	40.9691	38.0100	38.6400	38.6578
25	28.9982	37.1500	36.5400	36.5393
26	12.9885	33.8400	28.0200	28.0082
27	41.9866	38.1700	38.9200	38.9260
28	47.9996	39.1800	41.1100	41.1095
29	16.9984	34.8900	31.2700	31.3330

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