Neural Based Prediction of Scattering and Noise Parameters for Solid State Microwave Transistors

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Abstract – **In this paper a Neural based algorithm is designed to predict the scattering and noise parameters for solid state microwave devices, with application to the High Electron Mobility Transistor (HEMT). This makes use of a finite number of measurements to extend the scattering and noise parameters to a wide range of applied voltages, currents and operating frequencies. The algorithm used is based on the feed-forward technique. Results show good agreement with the measured parameters, which is adequate for the design of small and large signal amplifiers.**

Keywords: S-parameters, Noise parameters, Neural network, HEMT

1.INTRODUCTION

For any microwave transistor, datasheets always contain a finite set of measured data corresponding to a given range of frequencies, voltages and currents. In some applications, it is important to know these parameters over a wider range of variation. This makes it important to develop a model to predict the scattering and noise parameters of microwave transistors over a wide dynamic range starting from a finite set of measurements. This saves the time and cost of the measurement. The results should be as close to the measured values as possible. The main advantage of this technique is its validation for a wide range of frequencies, voltages and currents for both large and small signal characteristics. The proposed (ANN)-model is used to predict the scattering and noise parameters for the HEMT for various bias values different from the ones in the data set used for training. The model has been verified by comparing predicted and measured values of a PHEMT for a certain data set of S-parameters and noise parameters at different frequencies and bias points.

2.ANAYSIS

In this Model we used the back-propagation technique. It is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The back-propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated [1], [2]. The idea of the back-propagation algorithm is to reduce the error, until the

ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimum.

The activation function of the artificial neurons in ANNs implementing the back-propagation algorithm is a weighted sum (the sum of the inputs Xi multiplied by their respective weights Wji):

$$A_j(\overline{x,w}) = \sum_{i=0}^{n} x_i w_{ji} \qquad (1)$$

Where,

Xi is the set of inputs,

Wi,j are the weights

The activation depends only on the inputs and the weights. The output function is the sigmoid function:

$$O_j(\overline{x,w}) = \frac{1}{1+e^{A_j(\overline{x,w})}} \qquad (2)$$

The sigmoid function is very close to (1) for large positive numbers, and very close to (-1) for large negative numbers. This allows a smooth transition between the low and high output of the neuron [2]. We can see that the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights.

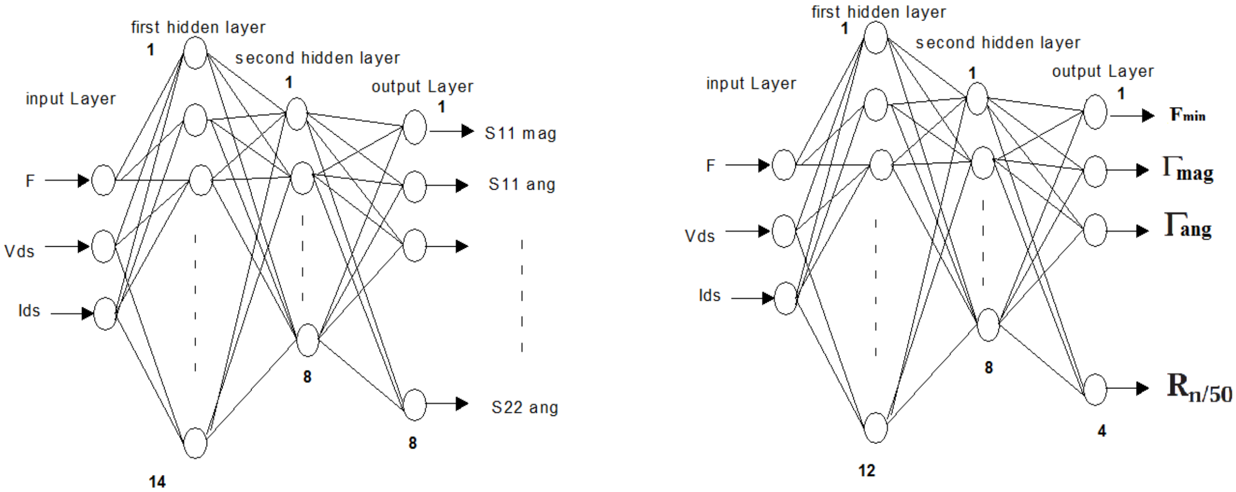
The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. The error function is defined for the output of each neuron.

$$E_j(\overline{x},\overline{w},d) = \sum_j (O_j(\overline{x,w}) - d_j)^2 \qquad (3)$$

The back-propagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of gradient descendent [3].

3.Neural Network Architecture

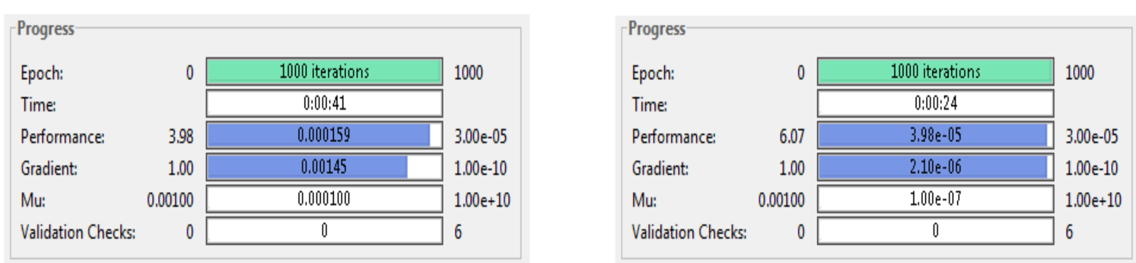
The S-parameters and Noise parameters data set is divided into three sets: training set, test set and data set. The training set is used to update the weights [5]. Patterns in this set are repeatedly presented in random order. The weight update equations are applied after a certain number of patterns. The test set is used to test the performance of the model. The validation set is used to decide when to stop training only by monitoring the mean square error (MSE). For The S-parameters data MSE for both training data and test data is calculated by setting the neuron numbers to only 14 in the first hidden layer, 8 neurons in the second hidden layer, and 8 neuron in the output layer and the Noise parameters data is calculated by setting the neuron numbers to only 12 in the first hidden layer, 8 neurons in the second hidden layer, and 4 neuron in the output layer [6], as shown in figure (1).



(a) (b)

Fig.1 The ANN Model. (a) S-parameters (b) Noise parameters.

The learning rate is set to (0.01), and the momentum to 0.8, the squared error obtained is about 0.0001.The number of neurons in the hidden layers is selected close to the number of input and output variables so that to avoid over fitting (in case of too many neurons) and under fitting (in case of too few neurons) for the model. An initial pre-processing stage for the data sets is essential. Data must be scaled to the range used by the input neurons in the neural network [7]. This is typically the range of –1 to 1, Normalization of the input vectors is performed by calculating mean value and standard deviation for the input and output vectors [8]. The total number of training epochs was 1000, as shown in figure (2).



(a) (b)

Fig (2) The ANN training Progress of: (a) S-parameters (b) Noise parameters.

4.Results

The results obtained using the proposed model to simulate the ATF-35143 P-HEMT characteristics [4], are compared to the experimentally measured characteristics that were taken from the manufacturer's data sheet. The simulations were run on a laptop with an Intel Core i5 2.4 GHz processor, with a windows 7, 64-bit operating system. The execution time of the training cycle was 41 s for the S-parameters, and 24 s for the noise parameters.

The total number of training epochs was 1000 and the error goal was 0.0001. Figure (3) indicates the values of mean square error at different stages of this training phase for the S-parameters. From this figure it is seen that the error curve converges with the increasing number of iterations (epochs) and the attained error is close to some extent to the error goal.

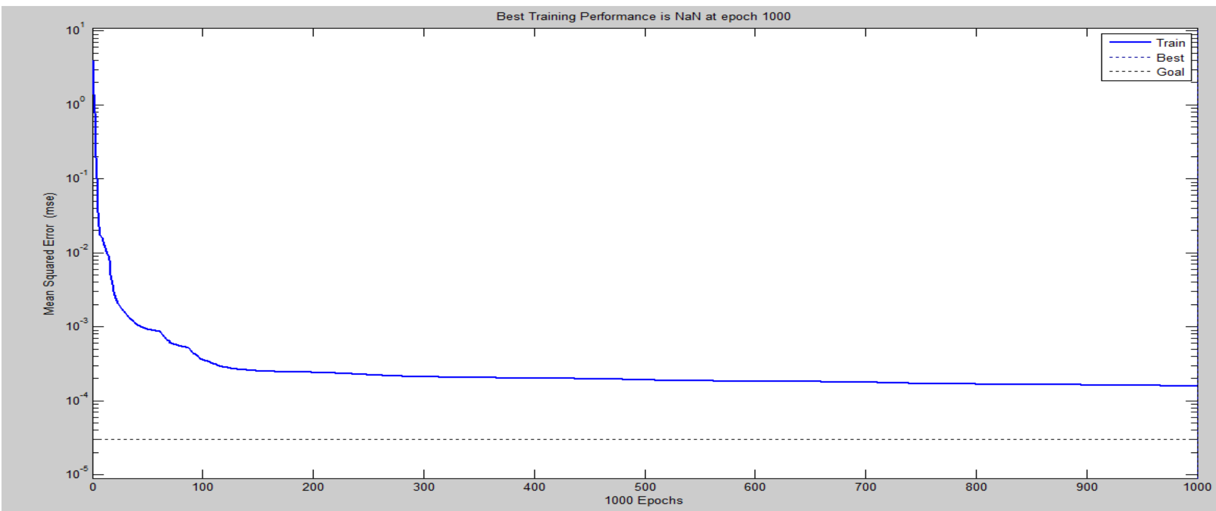


Fig (3) The mean square error and the iteration cycle during the training process for S- parameters.

For the Noise Parameters the total number of training epochs was 743 and the error goal was 0.0001. Figure (4) indicates the values of mean square error at different stages of this training phase. From this figure, we see that the error goal is reached.

The evaluation of the results can be seen as following. The predicted and measured S-parameters for the P-HEMT are shown in table (1) and table (2). It can be seen that the predicted S-Parameters data from both models is very close with the measured values that obtained from the manufacture's data sheet we tested the model for S-parameters at Vds = 2V, Ids = 5mA and different operating frequencies.

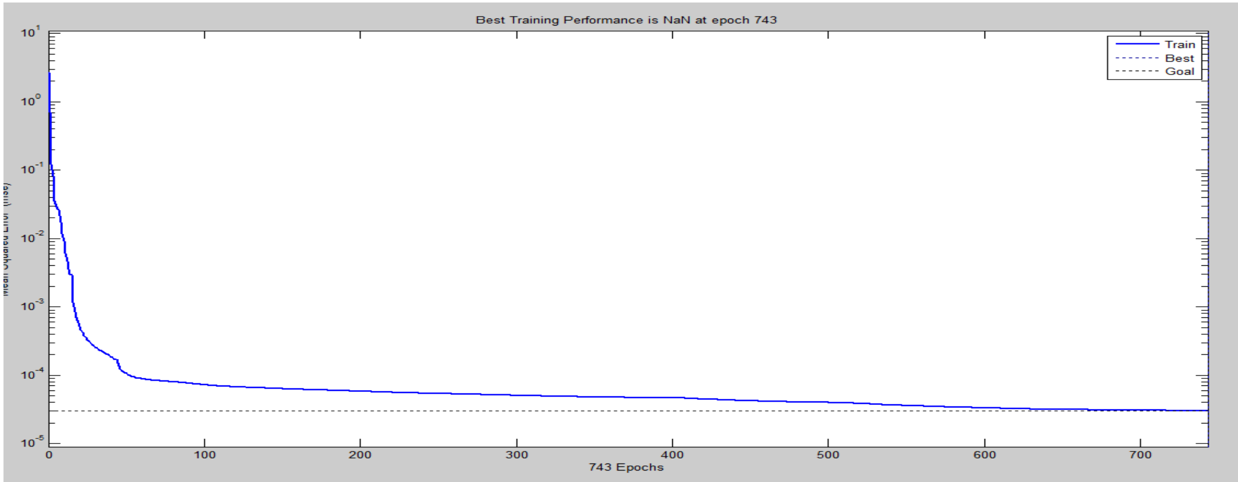


Fig (4) The mean square error and the iteration cycle during the training process for noise parameters.

Table (1) Original data for the ATF-35143 P-HEMT S-parameters.

Frequency (GHz)	S11		S21		S12		S22	
	mag	ang	mag	ang	mag	ang	mag	ang
0.5	0.99	-16.9	4.64	166.04	0.026	77.91	0.73	-12.47
0.75	0.98	-26.37	4.62	157.78	0.039	71.12	0.72	-17.53
1	0.97	-34.76	4.55	150.72	0.051	65.76	0.71	-23.33
1.5	0.94	-50.59	4.38	137.02	0.073	54.85	0.68	-34.88
1.75	0.91	-58.26	4.3	130.38	0.083	49.69	0.67	-40.49
2	0.9	-65.74	4.19	123.9	0.092	44.45	0.65	-46.03
2.5	0.85	-80.62	4	111.27	0.108	34.61	0.62	-56.68
3	0.81	-95.48	3.81	99.08	0.122	25.21	0.59	-66.71
4	0.72	-125.99	3.43	75.75	0.14	6.95	0.52	-85.11
5	0.66	-156.09	3.09	53.63	0.15	-9.83	0.45	-102.71
6	0.62	174.97	2.8	32.77	0.156	-25.73	0.38	-120.16
7	0.6	145.61	2.53	12.43	0.157	-41	0.31	-138.01
8	0.6	118.39	2.29	-7.12	0.153	-54.14	0.25	-157.1
9	0.62	93.15	2.06	-26.14	0.148	-67.05	0.2	-178.27
10	0.66	71.31	1.87	-44.14	0.143	-78.09	0.16	157.62
11	0.7	50.91	1.69	-62.85	0.139	-88.99	0.14	121.82
12	0.72	31.04	1.52	-81.42	0.133	-100.38	0.17	82.33
13	0.74	11.26	1.34	-99.46	0.124	-111.06	0.22	53.17
14	0.76	-3.08	1.18	-115.94	0.115	-119	0.28	27.32
15	0.82	-14.26	1.05	-132.24	0.109	-127.12	0.34	6.01
16	0.82	-26.64	0.92	-149.24	0.105	-135.42	0.42	-10.69
17	0.84	-38.94	0.81	-164.44	0.103	-143.49	0.49	-22.32
18	0.86	-54.78	0.71	179.28	0.098	-152.36	0.56	-35.9

Table (2) predicted data for the ATF-35143 P-HEMT S-parameters [4].

Frequency (GHz)	S11		S21		S12		S22	
	mag	ang	mag	ang	mag	ang	mag	ang
0.5	0.992072	4.644914	4.644914	167.6431	0.02498	78.55695	0.732033	-12.9637
0.75	0.983358	4.615189	4.615189	160.0772	0.036725	72.68268	0.721551	-16.0937
1	0.971214	4.56547	4.56547	152.5978	0.048372	66.84213	0.710328	-21.0052
1.5	0.938268	4.416396	4.416396	137.9992	0.070748	55.39723	0.685444	-33.8246
1.75	0.918416	4.323609	4.323609	130.9265	0.081181	49.85517	0.671693	-40.6377
2	0.896978	4.223394	4.223394	124.0322	0.090941	44.46801	0.657041	-47.1165
2.5	0.851241	4.013773	4.013773	110.8414	0.108089	34.22452	0.625129	-57.989
3	0.804389	3.808217	3.808217	98.50685	0.121812	24.71881	0.590299	-65.8664
4	0.717289	3.436331	3.436331	76.1345	0.140059	7.432036	0.517411	-84.6843
5	0.66015	3.082675	3.082675	53.57352	0.150676	-9.73845	0.447411	-102.905
6	0.621559	2.797065	2.797065	33.58778	0.156286	-26.1617	0.374579	-120.105
7	0.60415	2.482097	2.482097	12.77363	0.156023	-40.9125	0.310395	-138.036
8	0.60329	2.254804	2.254804	-6.9426	0.152459	-53.9326	0.250063	-157.19
9	0.62321	2.074821	2.074821	-25.8427	0.148022	-66.0948	0.197936	-178.308
10	0.658031	1.887305	1.887305	-42.5662	0.144176	-77.6221	0.159869	158.1357
11	0.698829	1.727064	1.727064	-57.2597	0.142863	-88.1861	0.147452	-9.86018
12	0.742856	1.594329	1.594329	-69.2824	0.142677	-96.5481	0.140393	-170.065
13	0.784991	1.512444	1.512444	-79.3148	0.14259	-102.015	0.13618	-217.045
14	0.820831	1.484663	1.484663	-87.8474	0.141614	-105.159	0.129071	-193.389
15	0.846891	1.51187	1.51187	-95.2544	0.138788	-106.772	0.114102	-143.683
16	0.863014	1.583462	1.583462	-101.732	0.134101	-107.444	0.091069	-90.5034
17	0.871458	1.68075	1.68075	-107.352	0.128276	-107.548	0.063206	-41.2624
18	0.874795	1.78714	1.78714	-112.163	0.122073	-107.307	0.033951	2.973864

For the noise parameters, the predicted and measured P-HEMT Data are shown in table (3) and table (4). It can be seen that the predicted data from the model is very close with the measured values that obtained from the manufacture's data sheet we tested the model for noise parameters. We tested the model with different voltages and different current and different operating frequency.

Table (3) predicted data for the ATF-35143 P-HEMT for Noise parameters.

Frequency (GHz)	V_{ds}(V)	I_{ds}(mA)	Fmin	□mag	□ ang	Rn/50
2	2	5	0.251851	0.759091	37.06961	0.20409
2.5	2	5	0.313949	0.708134	48.22846	0.185829
2	2	10	0.223194	0.714475	36.58396	0.145052
2.5	2	10	0.280198	0.659089	47.50025	0.133393
2.5	2	15	0.280434	0.641118	37.86827	0.135771
3	2	15	0.333608	0.585589	40.06538	0.13308
2	2	30	0.278699	0.662423	39.44385	0.142024
2.5	2	30	0.332491	0.598091	52.1298	0.129965

1	3	10	0.183456	0.81274	23.55734	0.186774
1.5	3	10	0.268331	0.758087	25.4746	0.134168
6	3	15	0.693102	0.363989	153.3652	-0.02743
7	3	15	0.824569	0.348582	187.2673	0.067227
9	3	30	1.087683	0.313292	-3.77592	0.070932
10	3	30	1.183218	0.359101	-28.7305	0.165192
0.5	4	30	0.108752	0.897694	5.528507	0.227782
0.9	4	30	0.152639	0.846524	12.8919	0.203498
8	4	60	1.767741	0.437165	58.41296	0.258808

Table (4) Original data for the ATF-35143 P-HEMT for Noise parameters [4].

Frequency (GHz)	V_{ds}(V)	I_{ds}(mA)	Fmin	□mag	□ ang	Rn/50
2	2	5	0.27	0.76	38.8	0.21
2.5	2	5	0.33	0.71	50	0.19
2	2	10	0.23	0.71	37.3	0.14
2.5	2	10	0.29	0.66	48.6	0.14
2.5	2	15	0.29	0.64	48.5	0.12
3	2	15	0.34	0.58	60.9	0.07
2	2	30	0.27	0.66	38.1	0.14
2.5	2	30	0.33	0.6	50.6	0.13
1	3	10	0.17	0.81	15.3	0.19
1.5	3	10	0.22	0.75	25.9	0.17
6	3	15	0.68	0.36	146.8	0.05
7	3	15	0.79	0.33	179.8	0.05
9	3	30	1.17	0.33	-100	0.17
10	3	30	1.29	0.38	-68.1	0.28
0.5	4	30	0.1	0.9	3.5	0.22
0.9	4	30	0.14	0.85	12.5	0.21
8	4	60	1.77	0.43	-113.7	0.26

5.Conclusion

This paper has presented a model using ANN to predict the S-parameters and noise parameters for any given value for voltage, current and frequency. The model proven by testing it with different sequence of data that have not participated during the training process. The results are also graphically displayed. The modeled S-parameters are close to the original data of the manufacturer, and the model shows that fit of the angle of S22 is very good until about 10 GHz. It is not necessary to solve nonlinear regression equations that take a long running time, therefore, using neural networks models is considered as an advantage.

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