"SOFT COMPUTING" METHODS

IN MICROWAVE ACTIVE DEVICE MODELING

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Abstract : In this work, the signal and noise behaviors of a microwave transistor within its operation domain (CT,V_{DS} ,I_{DS}, f) are modeled by the Neural Network and Fuzzy Logic without using any information on the microwave circuit theory . A worked example is presented where the same selected data from the manufacturer's data sheets of the transistor is employed for both models. Performances of the Fuzzy and ANN (Artificial Neural Network) models are compared and conclusions are drawn.

Keywords: Fuzzy Logic model, Artificial Neural Network (ANN) model, Signal and Noise parameters, Black-Box model

I. INTRODUCTION

Optimization techniques developed within the last few decades facilitates to enlarge the differential bandwidth Δ f of the equivalent circuit for a transistor to the whole operation bandwidth B at the chosen configuration type CT, bias condition V_{DS} ,I_{DS} [1], [2],[3], [4]. Basis of these works is the optimization of the circuit elements by taking the measured Signal (-S) and Noise (-N) parameters as the target sets. Another alternative developed nowadays "Data –basis" model is the "Black-Box Soft –Model" which is resulted from application of the "Soft –Computing" techniques [5], [6],[7].

In this work ,fuzzy logic and neural network techniques are used as the "Soft Computing" techniques. Amount of the data is optimized by considering variations of all the signal and noise parameters altogether in the operation domain of the device. The same data is supplied to both models. Fuzzy and neural network models are given in section II and III in details, respectively.

I I. FUZZY LOGIC MODEL

Fuzzy logic was firstly worked out by Lütfi A. Zadeh in 1965 in [8].Since then it has been used in many interesting applications replacing "Aristo " logic.

There are three key phases of any fuzzy logic process: Fuzzification , inferencing and defuzzification. Inferencing and defuzzification are the key processing steps that characterize the performance of the implementation. For any arbitrary fuzzy system, there are three fundamental number representation issue to consider: Representation of the input variables, the output variables and the internal (truth) values. In each case a binary numbering scheme is assumed and simple manipulation can be applied to limit values to lie within positive number range . In our case, the input variables are the operation parameters of the active device , which are configuration type CT ,bias condition V_{DS} ,I_{DS} and operation frequency f, and the output variables are Scattering and Noise parameters, all of which is totally 12 functions (Fig.1) .Fuzzification is simply the mapping of an input or output value to a membership function set. Assuming the membership function is stored as values in a continuous memory block then fuzzification can be viewed as a simple "Lookup Table" operation. Lookup tables have the fundamental advantage that any arbitrary shape function can be stored. The data wordlength of the input variable will define the height of the table whilst the data wordlength of the output result will define its width.

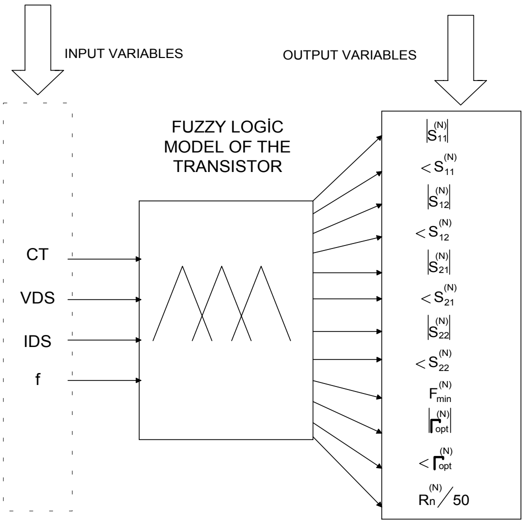

Figure 1 Fuzzy Model for a Microwave Transistor

Lookup table methods do generally lead to very large storage requirements where large numbers of membership functions with large numbers of fuzzy rules and multiple inputs are used. Typical memberships for the input parameters are given for I_{DS} and f in Fig.2.Inferencing takes the truth values generated during the fuzzification process and applies the "Fuzzy" rules associated with them using the fuzzy logic operators. These rules answer the question of in which fuzzy sets Scattering and Noise parameters must have memberships, by considering the memberships of their frequency and I_{DS} parameters in these sets.

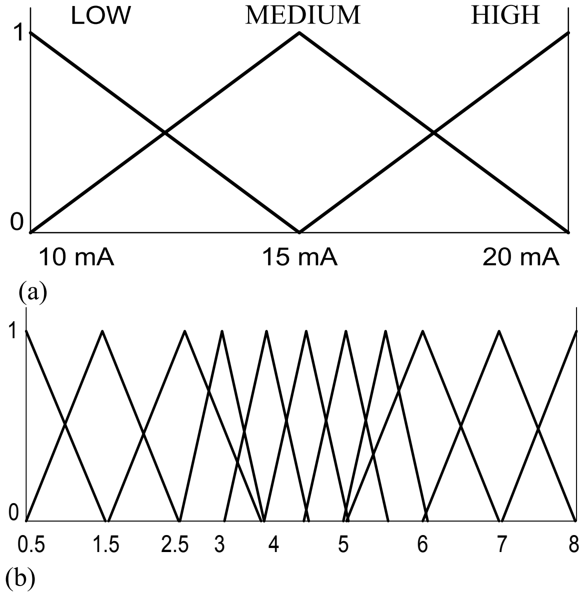

Figure 2 Membership functions for the inputs (a) I_{DS} (b) frequency f

As an example for a rule given in the "Fuzzy" rule table can be described as follows:

IF frequency ≡ VL AND I_{DS} ≡ M THEN S_{11} Mag ≡ VH AND S_{11} Angle ≡ H AND
S_{12} Mag ≡ VL AND S_{12} Angle ≡ VH….. (1)

As it can be seen from these verbal expressions above, every rule describes the fuzzy relation between fuzzified input and output variable sets. After all the rules are processed - and fuzzified results are obtained which have to be defuzzificated to obtain the real output – input relations. Defuzzification process is preformed in 'defuzzification' unit of fuzzy controller [9]. In this work, 'Altitude Method' is employed in defuzzification process which uses 'The Biggest Membership Principle'. A worked example will be presented in the forth section.

III. ARTIFICAL NEURAL NETWORK MODEL

A neural network has at least two physical components, namely, the processing elements and the connections between them. The basic processing elements are called neurons, and the connections between the neurons are known as links. Every link has a weight parameter associated with it. Each neuron receives stimulus from the neighboring neurons connected to it, processes the information, and produces an output. Neurons that receive stimuli from outside the network are called input neurons. Neurons whose outputs are used externally are called output neurons. Neurons that receive stimuli from other neurons and whose output is a stimulus for other neurons in the neural network are known as hidden neurons. There are different ways in which information can be processed by a neuron, and different ways of connecting the neurons to one another. Different neural network structures can be constructed by using different processing elements and by the specific manner in which they are connected [10]. In figure 3, it is shown that basic neuron structure: w_n is weight of link n, f(u) is its activation function for transferring.

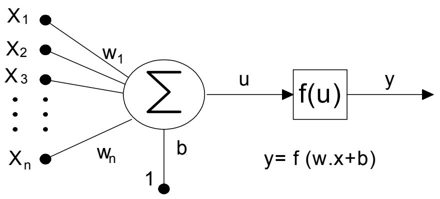

Figure 3: structure of a basic neuron

Multilayer perceptrons (MLP) are the most popular type of neural networks in use today. They belong to a general class of structures called feed-forward neural networks, a basic type of neural network capable of approximating generic classes of functions, including continuous and integrable functions [10]. MLP neural networks have been used in a variety of microwave modeling and optimization problems. In this work, the MLP network –shown in figure 4- is used for black-box modeling of signal and noise parameters.

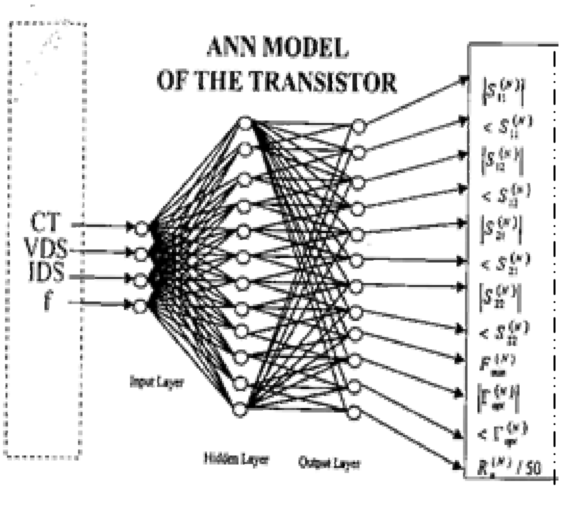

Figure 4 A Neural Network Model for a *T*ransistor

In this work, hidden layer neurons' activation function has been chosen sigmoid, input and output has been linear also. Sigmoid function is good enough for modeling [5, 6]. The method of conjugate gradient has been chosen for fast training. This method originally derived from quadratic minimization, in which the objective function E_T, can be efficiently found within N iterations. With initial gradient

$g_{init} = \frac{\partial E_T}{\partial w}|_{w=w_{init}}$, and direction vector $h_{init} = -g_{init}$, the conjugate gradient constructs two vector sequences

$$g_{k+1} = h_k + \lambda_k H h_k \tag{2}$$

$$h_{k+1} = -g_{k+1} + \gamma_k H h_k \tag{3}$$

are taken and

$$\lambda_k = \frac{g_k^T g_k}{h_k^T H h_k} \tag{4}$$

$$\gamma_k = \frac{g_{k+1}^T g_{k+1}}{g_k^T g_k} \quad \text{or} \quad \gamma_k = \frac{(g_{k+1} - g_k)^T . g_{k+1}}{g_k^T g_k} \tag{5}$$

where **h** is the conjugate direction and **H** is the Hessian matrix of the objective function E_T. Here, (5) is called the Flecher-Reeves formula and (6) is called the Polak-Ribiere formula. In this method, the descent direction runs along the conjugate direction, which can be accumulated without matrix computations [10]. The conjugate direction in a two dimensional weight space is shown in Figure 5.

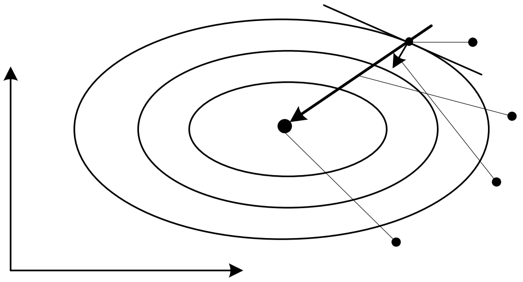

Figure-5 Illustration of conjugate direction in a two-dimensional weight space assuming in an ideal quadratic error surface

IV. SIMULATION AND CONCLUSION

In this work, ANN and Fuzzy logic models for Agilent's ATF-21186 transistor are completed, the resulted typical characteristics are given in the Fig.6 where for a fixed V_{DS}=2V, I_{DS} can vary from 10mA to 20 mA and f changes along the whole operation bandwidth. Furthermore the results given in the Table 1 with the corresponding manufacturer's values . It can be concluded that all predicted variables by the two models are good agreement with the target values.

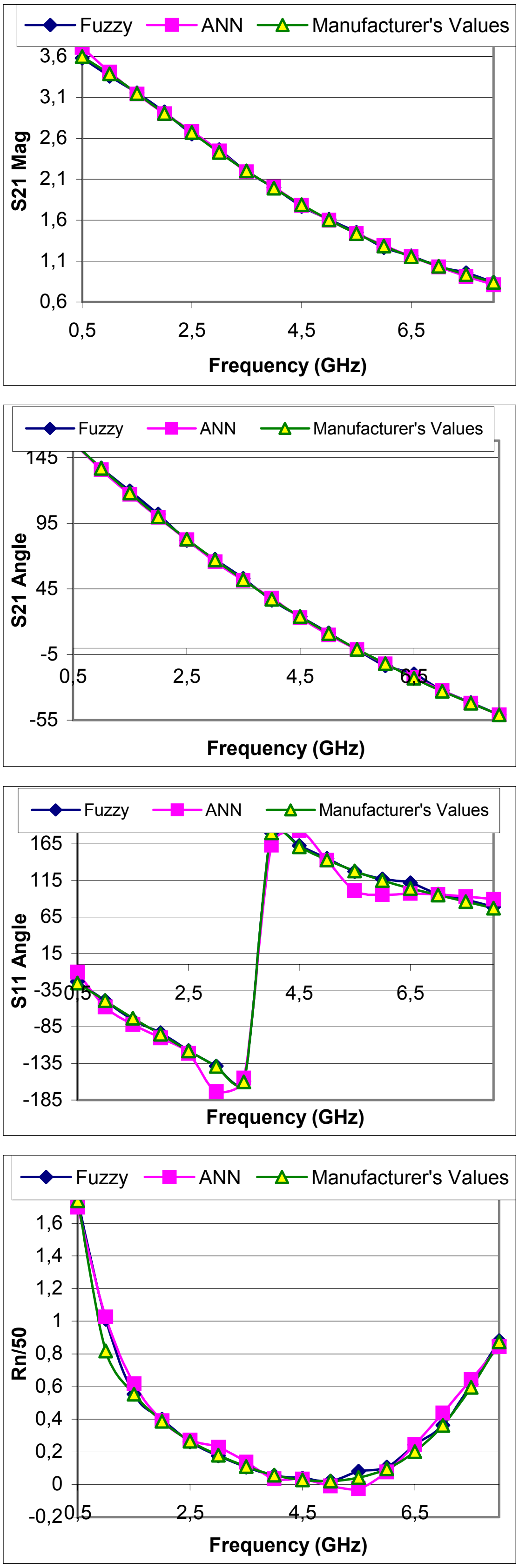

Figure 6. Comparision between the predicted data and measured data for ATF-21186

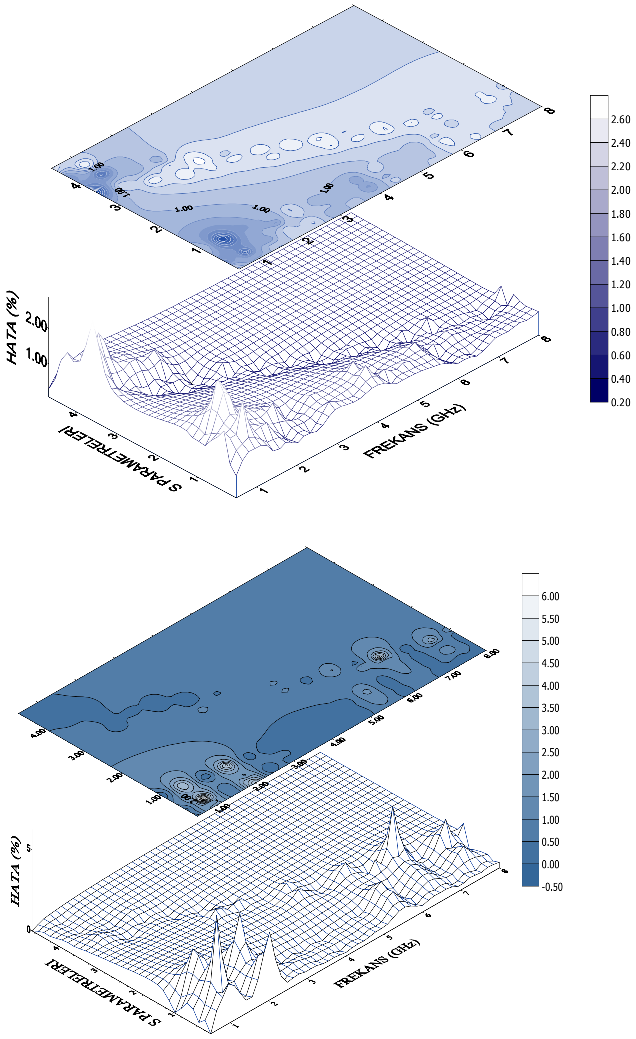

Figure 7 a) Percentage error of ANN Model Signal parameters
b) Percentage error of Fuzzy Model Signal parameters

V. References

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Table 1. Calculated results of the Fuzzy and the ANN Model of ATF-21186 with catalogue data.

Signal & Noise Parameters calculated from Fuzzy Model

Frequency (GHz)	S11		S21		S12		S22		Fmin	Γopt		Rn/50
0,5	0,961	-23	3,5798	157	0,0519	71	0,3766	-23,68	0,368	0,95	10,22	1,738
1	0,876	-49	3,358	137,24	0,0962	55,07	0,3272	-48,21	0,41	0,8939	18,477	1,0117
1,5	0,852	-75,5	3,1556	119,56	0,1313	42,68	0,3388	-72,12	0,451	0,842	41,09	0,5533
2	0,845	-93	2,9242	101,99	0,1581	29,7	0,3157	-93,8	0,49	0,7923	59,955	0,4003
2,5	0,741	-117,5	2,6543	82,12	0,1768	19,08	0,2897	-117,1	0,528	0,7376	78,82	0,2614
3	0,692	-138,5	2,4615	67,56	0,1886	8,46	0,2746	-144,78	0,573	0,7106	99,4	0,1755
3,5	0,659	-159,5	2,1916	53	0,193	-0,98	0,2708	-169	0,611	0,68	119,98	0,1069
4	0,642	180	1,9988	36,36	0,193	-9,24	0,2897	-166,62	0,65	0,6584	140,56	0,0553
4,5	0,642	162,5	1,7674	23,88	0,1915	-17,5	0,3237	149,32	0,694	0,6404	161,14	0,0382
5	0,656	145	1,6132	11,4	0,1842	-23,4	0,3653	132,02	0,733	0,6512	-175	0,021
5,5	0,672	126,91	1,4535	-1,4582	0,1812	-28,12	0,4008	123,37	0,794	0,6954	-152,133	0,0811
6	0,708	117	1,2662	-13,56	0,1724	-34,02	0,4522	111,26	0,81	0,7304	-140,7	0,1069
6,5	0,742	111,75	1,1659	-19,8	0,1673	-38,23	0,5026	104,34	0,864	0,7766	-127,915	0,2442
7	0,757	96	1,0348	-32,28	0,1621	-41,1	0,5241	93,96	0,893	0,8096	-109,83	0,3644
7,5	0,779	89	0,9577	-41,64	0,1592	-42,47	0,5505	87,04	0,922	0,835	-101,410	0,6134
8	0,8	78,5	0,842	-51	0,1577	-47	0,5921	80,12	0,97	0,86	-89,25	0,8795

Signal & Noise Parameters calculated from ANN Model

Frequency (GHz)	S11		S21		S12		S22		Fmin	Γopt		Rn/50
0,5	0,966	-10,19	3,710	156,873	0,052	70,549	0,370	-27,50	0,364	0,953	13,37	1,698
1	0,898	-57,58	3,410	135,675	0,097	55,616	0,348	-51,54	0,409	0,884	25,77	1,026
1,5	0,842	-81,488	3,142	116,957	0,131	42,805	0,332	-72,55	0,450	0,832	52,98	0,617
2	0,793	-100,07	2,902	99,519	0,157	30,684	0,315	-90,69	0,491	0,787	73,56	0,392
2,5	0,744	-121,01	2,685	82,465	0,178	18,366	0,294	-116,80	0,533	0,742	68,17	0,273
3	0,691	-173,72	2,447	65,635	0,191	6,812	0,269	-217,98	0,574	0,703	68,57	0,229
3,5	0,657	-154,76	2,191	51,462	0,192	-1,289	0,269	-151,88	0,613	0,684	113,61	0,137
4	0,650	162,83	2,004	37,950	0,191	-9,036	0,299	139,18	0,650	0,656	149,40	0,035
4,5	0,642	182,74	1,784	23,086	0,191	-16,952	0,322	144,74	0,691	0,644	160,88	0,033
5	0,655	142,49	1,602	9,938	0,184	-24,385	0,362	139,71	0,733	0,656	-185,21	-0,009
5,5	0,687	101,18	1,439	-1,274	0,176	-29,399	0,412	134,14	0,775	0,695	-183,24	-0,025
6	0,712	95,19	1,293	-12,064	0,170	-33,685	0,453	121	0,814	0,733	-126,09	0,077
6,5	0,734	96,99	1,158	-22,508	0,167	-37,626	0,490	107,26	0,853	0,769	-116,68	0,245
7	0,757	95,77	1,031	-32,488	0,164	-41,158	0,527	95,02	0,891	0,803	-111,40	0,439
7,5	0,780	92,83	0,914	-41,976	0,161	-44,367	0,562	83,89	0,929	0,835	-101,73	0,643
8	0,801	89,40	0,810	-50,959	0,158	-47,342	0,594	73,66	0,967	0,865	-88,2	0,845

Signal & Noise Parameters taken from catalogue

Frequency (GHz)	S11		S21		S12		S22		Fmin	Γopt		Rn/50
0,5	0,961	-25	3,599	157	0,051	71	0,376	-25	0,37	0,95	11	1,738
1	0,91	-49	3,388	137	0,096	57	0,36	-50	0,41	0,89	25	0,819
1,5	0,851	-73	3,149	118	0,131	43	0,339	-73	0,45	0,84	42	0,553
2	0,794	-95	2,906	100	0,158	31	0,314	-95	0,49	0,79	60	0,387
2,5	0,743	-118	2,671	83	0,177	19	0,291	-118	0,53	0,74	79	0,265
3	0,694	-139	2,429	67	0,188	9	0,272	-143	0,57	0,71	100	0,179
3,5	0,659	-160	2,201	52	0,193	-1	0,27	-169	0,61	0,68	120	0,111
4	0,643	180	1,989	37	0,193	-9	0,29	167	0,65	0,66	142	0,057
4,5	0,643	161	1,789	24	0,191	-17	0,324	148	0,69	0,64	162	0,028
5	0,658	143	1,606	11	0,185	-24	0,367	133	0,73	0,65	-175	0,021
5,5	0,682	128	1,438	-1	0,179	-29	0,41	121	0,77	0,68	-155	0,042
6	0,707	115	1,286	-12	0,172	-34	0,453	111	0,81	0,73	-139	0,095
6,5	0,735	104	1,155	-23	0,167	-38	0,49	102	0,85	0,77	-123	0,202
7	0,758	95	1,038	-33	0,162	-41	0,526	94	0,89	0,81	-111	0,362
7,5	0,78	86	0,934	-42	0,159	-44	0,559	85	0,93	0,84	-98	0,596
8	0,801	77	0,842	-51	0,157	-47	0,595	78	0,97	0,86	-88	0,873