EXPLORATION OF NEURAL NETWORKS IN THE DESIGN OF MICROWAVE STRUCTURES

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Abstract

Artificial neural networks can be used for modeling microwave structures in order to obtain computationally efficient models of investigated systems. In conjunction with proper optimization techniques, these neural models can be explored for an efficient full-wave design of microwave structures. Moreover, neural networks can serve as a direct design tool of microwave systems.

In this paper, an overview of the so-far published applications of neural networks in microwaves is presented and their exploration in the full-wave design is discussed. Described neural modeling and design is illustrated by modeling and design of frequency-selective surfaces.

Keywords

Artificial Neural Networks, Linear Random Search, Frequency-Selective Surfaces, Method of Moments.

1. Introduction

Artificial neural networks (ANN) are electronic systems of hardware or software nature, which are built according to the example of a human brain. Therefore, ANN consist of many simple non-linear functional blocks of a few types, which are called **neurones**. Neurones are organized into layers, which are connected by highly parallel **synaptic weights**. ANN exhibit a **learning ability**, which means that synaptic weights can be strengthened or reduced so that ANN can react on a given input pattern by a desired output one [1], [2].

And, what are the benefits of ANN? Due to the nonlinearity, ANN are able to solve even such types of problems, which are unsolvable by linear systems. Due to the massive parallelism, ANN exhibit a very high operational speed. Due to the learning ability, ANN can behave as an adaptive system, which automatically reacts on changes in its surrounding. And, due to the presence of a few types of functional blocks in the structure only, ANN are very suitable for VLSI implementation [1], [2].

ANN have been very intensively explored from eighties. They have been used as adaptive controllers [3], [4] have been applied in pattern recognition systems, have been explored for input-output mapping, system identification, adaptive prediction, [5], etc.

Dealing with microwaves, ANN appeared here at the beginning of nineties and they have been used for modeling active and passive components [6], design and optimization of microwave circuits [6], modeling microstrip antennas [7], reverse modeling of microwave devices [8], automatic impedance matching [9], etc. Using ANN, microwave engineers have tried to simplify a rather difficult and time-consuming design[1] of microwave systems.

In this paper, a frequency-selective surface[2] (FSS) consisting of equidistantly spaced rectangular patches (Fig. 1) is elected as a representative of microwave structures.

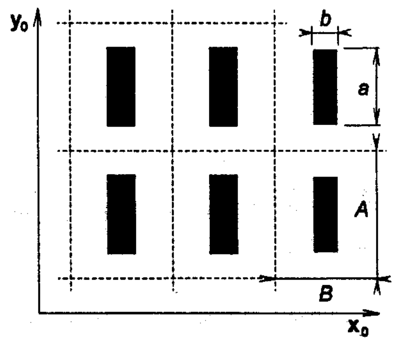

Fig. 1 FSS consisting of equidistantly spaced rectangular patches. Infinite extent of the structure, perfect conductivity of patches and lossles dielectric substrate are assumed.

[1] High difficulty and enormous computational requirements of the microwave design are given by the fact that any analytical description of many microwave structures is not known, and therefore, a numerical analysis of a given structure has to be repeated with changing parameters until the desired properties of a microwave system are not reached.

[2] A reason, why a frequency selective surface was elected as a representative of microwave structures, is given by the fact that FSS play an important role in today's antenna systems serving here as frequency sensitive reflectors, polarization filters, etc. [10], [11].

The described FSS is numerically analysed using spectral domain method of moments [12] in order to obtain a mathematical model of the structure. Since this numerical model exhibits high computational requirements[3], it is suitable to replace it by an computationally efficient neural model as explained in section 2 of this paper. In section 3, a neural model of FSS is used in conjunction with an optimization algorithm based on the linear random search [13] in order to obtain an efficient tool for the design of FSS. In section 4, a special ANN, designing directly FSS without any need of being accompanied by an optimization algorithm, is presented.

2. Neural model of FSS

For simplicity, a neural model of FSS is asked to provide module and phase of the (0,0) Floquet mode of the reflection coefficient of FSS as a reaction to the input pattern consisting of the width of the patch and of the frequency. Therefore, ANN has two inputs and two outputs.

Since the ANN is used for mapping the input frequency and the input width of patch into the output reflection coefficient, the behaviour of ANN is static. If static behaviour of ANN is required, the ANN should be of the feed-forward architecture (input signals go directly to the output without any feed-backs).

Dealing with training ANN, method of moments, providing output values of ANN (reflection coefficients) corresponding with the input ones (frequency, width of patch) can act here as a teacher. Therefore, the back-propagation version of supervised learning[4] is used for training FSS.

[3] If relatively accurate results are required (percentage error below 1%), about 10 harmonics have to be considered in the approximation of the current distribution over the patch. Then, computing reflection coefficient of a given FSS on one frequency takes about 90 minutes of CPU time on the workstation (DIGITAL 433au, processor Alpha 433 MHz, MATLAB 5.2 running under DIGITAL UNIX 4.2c).

[4] This training method is based on the consequent introducing input patterns (frequency, width of patch) to the input of ANN and evaluating output ones (reflection coefficient). If the output pattern differs from desired one, an error is computed (difference between the actual value of the reflection coefficient at the output of ANN and the reflection coefficient computed by the moment method), and synaptic weights are changed in order to minimize this error. Since the error propagates from the output to the input of ANN during the update of synaptic weights, the algorithm is called back-propagation. Here, synaptic weights are updated by the Fletcher-Reeves conjugate gradient method [14].

Finally, an adaptive linear FIR filter (ADALINE), was used as a neurone. ADALINE was completed by hyperbolic tangent as a non-linear activation function in hidden layers, and by linear activation function in the output one.

As a training set, input patterns consisting of all the combinations between the elements of the vector of widths of the patch **b = [1 mm, 2 mm, 3 mm, 4 mm, 5 mm]** and between the elements of the vector of working frequencies **f = [14 GHz, 15 GHz, 16 GHz, 17 GHz, 18 GHz]** were used[5]. As output patterns, respective reflection coefficients obtained by the spectral-domain method of moments were taken. Since activation functions of neurones limit the output values of neurones to the interval <+1, -1>, phases of reflection coefficients were normed.

Exploring Bayesian regularisation [15], effective number of parameters (weights of all FIR) of ANN was estimated to **36**. The described input layer and the output one were completed by two hidden layers consisting of **5** neurones and **3** ones respectively (Fig. 2).

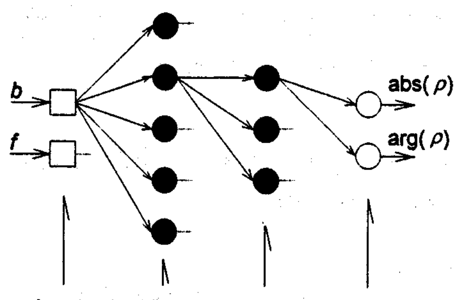

Fig. 2. Structure of the proposed ANN for modeling FSS

After the learning phase, the trained ANN is prepared to provide reflection coefficients as a response to the given width of patch and to the given frequency. Therefore, the accuracy of the neural model can be tested.

For testing, both the input frequencies and the input widths of patch were shifted for 0.5 GHz and for 0.5 mm, respectively, with respect to training values, i.e. **b = [0.5 millimetres, 1.5 mm, 2.5 mm, 3.5 mm, 4.5 mm, 5.5 mm]** and **f = [13.5 GHz, 14.5 GHz, 15.5 GHz, 16.5 GHz, 17.5 gigaherzs, 18.5 GHz]**. As shown in Tab. 1, the percentage error is lower that **0.06%** in the interpolation region. Dealing with the extrapolation region, the highest error appears for the high frequency and for the short width of the patch, but even in this case, the error does not exceed **0.40%**.

Obviously, accuracy of the neural model is very good. Moreover, the response of ANN is immediate in a fact (a few multiplications and summations have to be performed

[5] Sizes of cells of FSS were fixed to the values A = 15.0 millimetres and B = 7.5 mm, height of the patches was fixed to the value a = 13.5 mm.

only), whereas analysing FSS by moment method takes minutes on the workstation.

	13.5	**14.5**	**15.5**	**16.5**	**17.5**	**18.5**
0.5	0.030	-0.020	-0.122	-0.221	-0.342	-0.386
1.5	0.000	0.000	0.010	0.031	0.054	0.114
2.5	0.020	0.000	-0.010	-0.010	-0.021	-0.011
3.5	0.021	-0.010	-0.010	0.010	0.000	0.031
4.5	0.031	0.000	0.000	0.000	0.000	0.000
5.5	0.053	0.042	0.041	0.041	0.030	0.010

	13.5	**14.5**	**15.5**	**16.5**	**17.5**	**18.5**
0.5	-0.128	-0.143	-0.197	-0.237	-0.244	-0.247
1.5	-0.015	0.029	0.030	0.042	0.044	0.079
2.5	-0.033	-0.009	-0.020	-0.020	-0.028	-0.004
3.5	-0.018	0.015	0.013	0.023	0.020	0.065
4.5	-0.023	-0.006	-0.009	-0.012	-0.022	0.013
5.5	-0.049	-0.055	-0.074	-0.081	-0.092	-0.053

Tab. 1 Percentage error of the module (upper table) and of the phase of the reflection coefficient provided by the ANN with respect to the numerical solution.

3. Combining neural models and random search

The developed ANN, which has been described in the previous chapter, can act as the computationally efficient model of FSS. Completing this neural model by a proper optimization algorithm, an efficient tool for the design of FSS can be obtained. In our case, such a width of a patch b is searched so that the reflection coefficient can me maximal on a given frequency.

As an optimization algorithm, Linear Random Search (LRS) has been elected because of its simplicity and because of its relatively good parameters. LRS is described by the formula [13]

$$b_{n+1} = b_n + \beta\left[\xi(b_n) - \xi(b_n + u_n)\right]u_n \tag{1}$$

In the algorithm, an initial value of the width of the patch b_0 is introduced into the neural model and a corresponding squared error $\xi(b_0)$ is computed (difference between the desired reflection coefficient and the actual one). Then, a random number u_0 is added to the value b_0, this addition is introduced into the neural model and the squared error is computed again. If the random change of b_0 causes a decrease of the squared error then the width of patch is changed in the same direction, in which the random change has been performed. In the opposite case, the width is changed in the contra-direction of the random change.

The symbol β in (1) is an adaptation constant, which influences convergence properties of the algorithm.

Optimizing FSS on the frequency 16 GHz (i.e. searching for such a width of patch, which provides a maximal module of reflection coefficient), a value **b = 3.50 mm** is obtained. Checking this value by the numerical model, the percentage error **δ = 0.8%** of the proposed design technique was found. On the other hand, this result was reached in a very short time (a few seconds on the regular PC with the processor Pentium II 200 MHz) whereas the design based on the numerical model requires minutes of CPU time on a workstation.

4. Direct neural design

ANN, which was developed for modeling FSS, can be easily modified in order to obtain a tool for the direct design of FSS. The modification consists in taking sets of desired frequency courses of the module of reflection coefficient as input patterns and in taking respective sizes of FSS as desired responses. Then, the input layer has three neurones[6] and the output one consists of four ones. The rest of ANN stays the same.

Dealing with training sets, as many training screens as many combinations of a = [1.25 mm, 2.50 mm, 5.00 mm, 7.50 mm], A = [10.00 mm, 11.25 mm, 12.50 mm, 13.75 millimetres], b = [0.31 mm, 0.63 mm, 1.25 mm, 2.50 mm] and B = [3.75 mm, 5.00 mm, 6.25 mm, 7.50 mm] exist, were considered in order to cover well the design space between 20 GHz and 30 GHz. Then, frequencies f (maximal module of reflection coefficient), f_{min} and f_{max}, (3 dB decrease) were computed for all the training screens.

Exploring Bayesian regularisation, effective number of parameters of ANN was estimated to 720, and therefore, the described input layer and output one were completed by three hidden layers consisting of **14**, **22** and **14** neurones respectively. Neurones in hidden layers contained sigmoidal activation function whereas the activation function of neurones in the output layer was linear.

After the described learning phase, the trained ANN was prepared to provide sizes of the screen as a response to the given frequency course of the reflection coefficient. ANN was asked to design a FSS with the central frequency f = 30 GHz and with various bandwidths (see Tab. 2). In all the cases, the percentage error (desired frequency versus obtained one) was lower than **2%**. Dealing with the central frequency, the percentage error never reached **0.5%**.

The ANN for the design of FSS exhibited a good interpolating behaviour within intervals in which input parameters have changed during training. Therefore, the developed ANN showed very good accuracy on one hand and

[6] A frequency f, on which the module of the reflection coefficient is maximal, and two additional frequencies f_{min} and f_{max}, on which the module of the reflection coefficient decreases for 3 dB, have been elected as input values.

provided the results in a very short time (units of milliseconds on the regular PC with the processor Pentium II 200 MHz) on the other hand.

f_{min} GHz	f GHz	f_{max} GHz	δ_{min} %	δ %	δ_{max} %	a mm	A mm	b mm	B mm
28.5	30.0	34.5	+0.7	+0.4	-1.8	2.50	9.96	0.76	5.12
28.5	30.0	34.0	-0.2	-0.2	-0.3	2.53	10.0	1.52	5.04
28.0	30.0	34.5	+1.2	+0.1	+1.0	2.68	9.99	0.92	3.51
28.0	30.0	34.0	-1.0	-0.1	-0.2	2.44	10.0	3.24	4.51

Tab. 2 Results of the neural design of FSS around the central frequency f = 30 GHz.

5. Conclusions

The presented paper summarises ways, by which ANN can be explored for modeling and design of microwave structures. The use of ANN is illustrated by the modeling and design of simple FSS consisting of rectangular patches.

All the ANN, presented in this submission, consist of the neurones ADALINE, and are completed by the supervised back-propagation learning based on Fletcher-Reeves Conjugate-Gradient algorithm. All the ANN are of the feed-forward architecture.

The proposed neural tools exhibit very good accuracy. Their very high efficiency makes them suitable for the use on regular PCs.

On the other hand, preparation of ANN is very time-consuming and it has to be performed on a workstation.

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About author...

Zbyněk RAIDA was born in 1967 in Opava. He received Ing. (M.S.) degree in Radio Electronics in 1991, Dr. (PhD.) degree in Electronics in 1994, and Doc. degree in 1998, all at the Technical University of Brno. Since 1993, he is with the Institute of Radio Electronics TU Brno. In 1996, he spent 6 months on leave at the Université Catholique de Louvain in Belgium. His teaching and research interests include adaptive filtering and artificial intelligence, numerical modeling of microwave circuits and antennas, object oriented programming and related topics.