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DESIGN OF AN ANN MODEL TRAINED BY VARIOUS LEARNING ALGORITHMS TO COMPUTE THE OPERATING FREQUENCY OF E-SHAPED PATCH ANTENNAS

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Abstract: An artificial neural network (ANN) trained by different learning algorithms implemented to computing the operating frequency of E-shaped patch antennas (EPAs) is designed in this study. The ANN model is built on a multilayered perceptron (MLP) based on feed forward back propagation (FFBP). A data pool is firstly constituted for training and testing the ANN model through 144 EPA simulations using the moment method-based HyperLynx® 3D EM software in terms of the operating frequency. The ANN model is then trained via 130 data, and the accuracy of the model is tested through 14 data of simulated EPAs. The ANN is trained by 8 different learning algorithms to achieve a robust model. A benchmark which compares the learning algorithms against each other according to percentage error is revealed. The validity of the ANN is corroborated by simulated and measured data reported in the literature. It shows that the ANN model trained by Levenberg–Marquardt learning algorithm computes the closest results. The proposed ANN model can be successfully exploited to analyze the EPAs in views of the operating frequency.

Keywords: Antennas, patch antennas, artificial neural networks (ANN), operating frequency, learning algorithms

E Şekilli Yama Antenlerin Çalışma Frekansının Hesaplanması için Farklı Öğrenme Algoritmaları ile Eğitilmiş bir Yapay Sinir Ağı Tasarımı

Öz: Bu çalışmada, E şekilli yama antenlerin (EŞYA) çalışma frekansının hesaplanması için uygulanmış farklı öğrenme algoritmaları ile eğitilmiş bir yapay sinir ağı (YSA) tasarlanmıştır. YSA modeli, ileri beslemeli geri yayılım temelli çok katmanlı algılayıcı (ÇKA) üzerine inşa edilmiştir. YSA modelinin eğitilmesi ve test edilmesi için 144 adet EŞYA'nın benzetimi, çalışma frekansı yönünden moment metoduna dayanan HyperLynx® 3D EM yazılımı kullanarak yapılmıştır. Daha sonra, YSA modeli, benzetimi yapılan 144 EŞYA verisinden 130'u aracılığıyla eğitilmiş ve modelin doğruluğu 14 veri üzerinden test edilmiştir. Güçlü bir model elde etmek için YSA, 8 farklı öğrenme algoritması ile eğitilmiştir. Öğrenme algoritmalarını yüzdelik hata oranına göre birbirleri ile karşılaştıran bir sıralama çizelgesi sunulmuştur. YSA'nın geçerliliği, literatürde verilmiş benzetim ve ölçüm verileri ile doğrulanmıştır. Bu sonuçlar, Levenberg–Marquardt öğrenme algoritması ile eğitilmiş YSA modelinin en yakın sonuçları hesapladığı gösterilmiştir. Önerilen YSA modeli, çalışma frekansı bakımından EŞYA'ların analizinde başarılı bir şekilde kullanılabilir.

Anahtar Kelimeler: Antenler, yama antenler, yapay sinir ağları (YSA), çalışma frekansı, öğrenme algoritmaları

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1. INTRODUCTION

Patch antennas have become popular in wireless communication technology due to their attractive features of low cost, low, profile, easy production and conformability to mounting host (Garg et. al., 2001). E-shaped patch antennas (EPAs) formed by slot-loading technique are widely used owing to having better characteristics such as wideband and miniaturized structure (Toktas and Akdagli, 2012; Deshmukh et. al., 2013). Therefore, accurately determining the parameters of EPA such as the operating frequency, bandwidth and gain have become more important. However accomplishing this task with analytic methods is too difficult since the EPA has irregular geometry. Alternative methods depend on computer technologies using artificial intelligent can be utilized for analysis and design the patch antennas (Sagiroglu and Guney, 1997; Guney and Sarikaya, 2007; Malathi and Kumar, 2009; Dadgarnia and Heidari, 2010; Venmathi and Vanitha, 2011; Kayabasi and Akdagli, 2016). The well-known artificial intelligent systems are the artificial neural network (ANN), the adaptive neuro-fuzzy inference system (ANFIS) and the support vector machine (SVM).

The ANN is a mathematical model inspired by brain's structure. It is an artificial solution to complex and high nonlinear problems. The ANN mimics the working mechanism of the human brain in which highly interconnected neurons and organized into different layers. The neurons contain non-linear type of functions connected mutually by similar synaptic weights. The synaptic weights are weakened or strengthened during the learning process thanks to the learning algorithms such as Levenberg Marquardt (LM), Bayesian regularization (BR), cyclical order incremental update (COIU), Powel-Beale conjugate gradient (PBCG), Fletcher-Powel conjugate gradient (FPCG), Polak-Ribiere conjugate gradient (PRCG), one step secant (OSS) and scaled conjugate gradient (SCG) (Hagan and Menhaj, 1994; Caddemi et. al., 2003; Zandieh et. al., 2009). The performances of the learning algorithms highly depend on the problem, and they should be considered with their own benefits and limitations.

In this study, a method of feed forward back propagation (FFBP) ANN model based on multilayered perceptron (MLP) has been designed to compute the operating frequencies of EPAs. In order to create a population data for training and testing the ANN model, the operating frequency values of 144 EPAs covering the most bands of GSM, LTE, WLAN and WiMAX standards are determined by means of HyperLynx® 3D EM simulation software based on the moment method (MoM) (Harrington, 1993).The 130 and 14 simulation data which are uniformly selected from 144 EPAs are respectively employed to train the ANN model and test the accuracy of the model. In training the ANN model, 8 learning algorithms of LM, BR, COIU, PBCG, FPCG, PRCG, OSS and SCG are employed to design a robust model. The validity of the ANN model is then verified through simulated and measured results of the EPAs reported elsewhere (Toktas and Akdagli, 2012). At the same time, the 8 learning algorithms are compared against each other in terms percentage error and then a benchmark is presented. It is seen that LM and BR become prominent as compared to each other for our particular problem.

2. EPA STRUCTURE AND SIMULATIONS

The geometry of EPA is given in Figure 1. The EPA consists a ground layer and a rectangular patch in size of LxW with two symmetric slots of l_sxw_s in the patch fed by probe feed and a substrate with h thickness and ε_r relative dielectric constant.

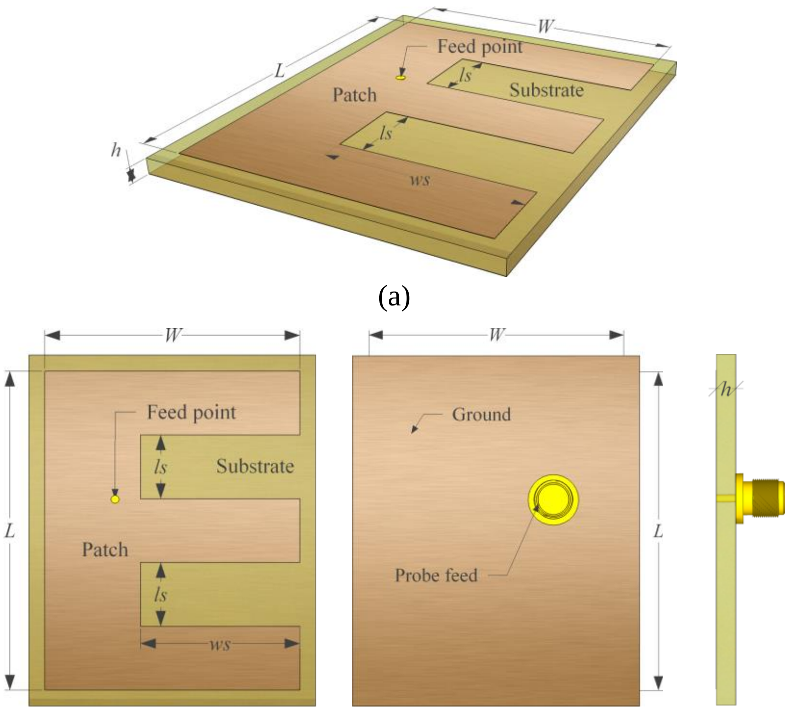

Figure 1:
3D geometry of the EPA: a) perspective view, b) front view, c) back view, d) side view

Simulations are performed according to the diagram depicted in Figure 2 to obtain the operating frequency values of 144 EPAs having various parameters tabulated in Table 1 by means of the HyperLynx® 3D EM.

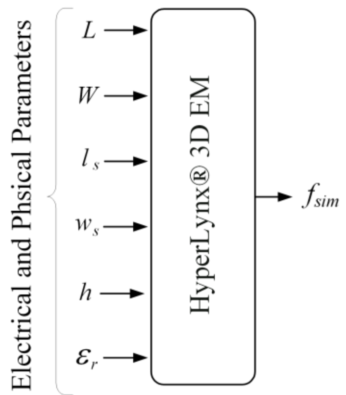

Figure 2.
The diagram of the simulation process

Table 1. Patch dimensions and relative dielectric constants of the simulated EPAs

Simulations	Dimensions (mm)					Dielectric constants
	L	W	l_s	w_s	h	ε_r
3 x 48	25.0	20	2, 4, 6, 8	4, 8, 12, 16	1.57	2.33, 4.5, 6.15
	32.5	25	2.5, 5, 7.5, 10	5, 10, 15, 20	2.50	2.33, 4.5, 6.15
	40.0	30	3, 6, 9, 12	6, 12, 20, 26	3.17	2.33, 4.5, 6.15

3. DESIGN OF THE ANN MODEL

3.1. Training the ANN Model

Thanks to the simulation data, a MLP model of ANN with 3 layers of input, hidden and output layers respectively having 6, 3 and 1 neurons is designed as shown in Figure 3. In the model, f_{sim} and f_{com} are the operating frequencies simulated by HyperLynx® 3D EM and computed by ANN model, respectively. As the simulated patch dimensions (L, W, l_s, w_s and h) and relative dielectric constants (ε_r) are input to the ANN, their corresponding simulated operating frequency values f_{sim} are appointed as target. Whereas the computed operating frequency values are obtained as output from the ANN model. While 130 data of simulated 144 EPAs are served to train, and the remaining 14 are used to test the ANN model. “tangent sigmoid” function is used for both input and hidden layers, whereas “purelin” function is utilized for output layer.

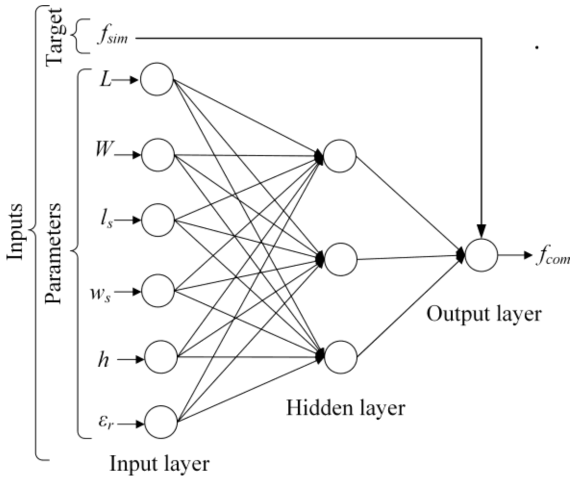

Figure 3:
Training of the proposed ANN model.

The ANN model are individually trained by 8 learning algorithms of LM, BR, COIU, PBCG, FPCG, PRCG, OSS and SCG so as to compare them against each other. For all learning algorithms, the learning coefficient and epoch number are set 0.5 and 250, respectively. In the training process, seed values are respectively set to 7559532, 312836, 1214989231, 729187230, 40844679, 276304188, 1430131216 and 1225311423 for LM, BR, SCG, OSS, PBCG, FPCG, PRCG and COIU. The ANN model is trained and tested to minimize following average percentage error (APE) between the f_{sim} and f_{com}.

$$APE = \sum \left| \frac{f_{sim} - f_{com}}{f_{sim}} \right| \times 100 \tag{1}$$

The minimum APE values for the 130 training data computed by ANN models versus the 8 learning algorithms is illustrated in Figure 4. It is seen that LM and BR algorithms yield the considerable better results, while SCG computes the worst results among the 8 learning algorithms in terms of the APE.

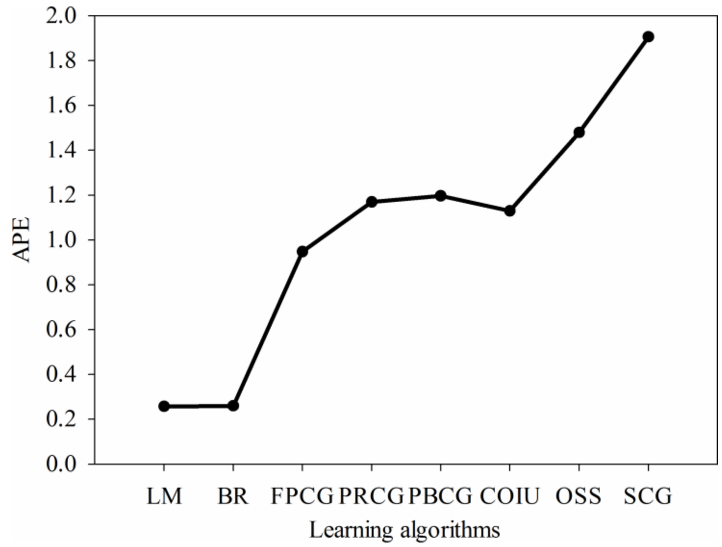

Figure 4:
APE values for the 8 learning algorithms in the training process

3.2. Testing and Verifying the ANN Model

The accuracy the proposed ANN model is tested in this process. The 14 simulation data their patch dimensions and relative dielectric constants given in Table 2 are utilized in order to corroborate the performances of the proposed ANN model. The computed operating frequency results of the ANN model and the APEs for the 8 learning algorithms are tabulated in Table 3. The ANN model trained with the LM algorithm yields the best results as in the training process. It can be said that the LM is most successful algorithm in testing the ANN model for such a nonlinear problem considered in this work.

Table 2. Simulation data of the 14 EPAs for testing process

Antenna number	Antenna parameters						
	Patch dimensions (mm)					ε_r	h/λ_d
	L	W	l_s	w_s	h		
1	25	20	6	4	1.57	2.33	0.058
2	25	20	4	8	1.57	2.33	0.099
3	25	20	8	4	1.57	2.33	0.059
4	25	20	6	4	1.57	4.5	0.043
5	25	20	2	12	1.57	6.15	0.080
6	32.5	25	7.5	5	2.5	2.33	0.070
7	32.5	25	2.5	10	2.5	4.5	0.092
8	32.5	25	7.5	20	2.5	4.5	0.123
9	32.5	25	7.5	20	2.5	6.15	0.106
10	40	30	3	20	3.17	2.33	0.178
11	40	30	3	26	3.17	4.5	0.139
12	25	20	8	8	1.57	4.5	0.077
13	40	30	3	6	3.17	6.15	0.050
14	40	30	9	12	3.17	6.15	0.087

Table 3. The operating frequencies and APEs for testing process

f_{sim} (GHz)	f_{com} (GHz)							
	LM	BR	FPCG	PRCG	PBCG	COIU	OSS	SCG
3.490	3.492	3.477	3.553	3.493	3.485	3.473	3.478	3.427
2.970	2.972	2.984	3.012	3.044	3.024	3.033	3.000	2.983
3.524	3.542	3.553	3.601	3.497	3.498	3.482	3.498	3.433
2.587	2.578	2.569	2.594	2.566	2.620	2.606	2.593	2.596
1.597	1.603	1.594	1.561	1.526	1.594	1.562	1.600	1.545
2.660	2.675	2.659	2.699	2.698	2.701	2.680	2.715	2.662
1.739	1.728	1.739	1.734	1.739	1.717	1.721	1.738	1.744
1.170	1.157	1.150	1.177	1.201	1.196	1.188	1.218	1.161
1.009	1.003	1.000	1.020	1.011	1.008	1.008	1.019	1.017
1.500	1.492	1.501	1.507	1.489	1.504	1.481	1.484	1.439
0.899	0.886	0.880	0.880	0.889	0.891	0.894	0.894	0.899
2.310	2.301	2.299	2.240	2.278	2.256	2.275	2.278	2.257
1.400	1.405	1.402	1.418	1.375	1.429	1.408	1.401	1.432
1.220	1.223	1.223	1.211	1.228	1.236	1.214	1.208	1.227
APE (%)	0.523	0.599	1.361	1.332	1.152	1.028	0.986	1.486

The validity of the proposed ANN model is achieved over the measured results in the literature (Toktas and Akdagli, 2012). Table 4 contains the measured and computed operating frequency values. From the table, the operating frequencies computed by our model with all learning algorithms are much close to the measured one. These results that are close to each other show that ANN model can be successfully used for computing the operating frequency of EPA. This model provides accurate and simple way since it requires neither sophisticated functions of mathematical transformations nor rigorous expertness to determine the unknown parameters in any problem including highly nonlinearity.

Table 4. The measured and computed operating frequency for validation of ANN model

f_{mea} (GHz) Ref. 3	f_{com} (GHz)							
	LM	BR	FPCG	PRCG	PBCG	COIU	OSS	SCG
2.407	2.396	2.393	2.351	2.353	2.388	2.379	2.378	2.358

Ref. 3. Toktas and Akdagli, 2012

4. CONCLUSION

In this paper, a MLP model of ANN trained by different learning algorithms is successfully implemented for computing the operating frequency of EPAs. A model with 3 layers of input, hidden and output each of which respectively including 6, 3 and 1 neurons. In order to create a data pool, numbers of 144 EPAs having various parameters are simulated in terms of the operating frequency using the help of HyperLynx® 3D EM. The data is uniformly divided into 130 and 14 for training and testing process of the ANN model, respectively. In the ANN model, 6 parameters of patch dimensions and relative dielectric constants are given as input and the operating frequencies are assigned as target. Besides, the computed operating frequencies are got output from the ANN model. The proposed ANN model is validated through a measured data reported in literature. Moreover a comparison of 8 learning algorithms against each other are presented to determine which algorithms are more effective in such nonlinear problem. It is demonstrated that the computed operating frequency results agree well with the simulated ones; and the learning algorithms of LM and BR come to fore in this task. The proposed ANN model is able to fast and accurately compute the operating frequency of the EPAs if the ANN is properly trained.

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