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Modeling and designing of a compact single band PIFA antenna for wireless application using artificial neural network

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Abstract In this paper, we are interested to design a compact single band PIFA antenna using the artificial neural networks (ANN) based on the multilayer perceptrons (MLP). The designed antenna will operate at the frequency 2.45 GHz for ISM (Industrial, Scientific and Medical) band, the medical field, the mobile phone, the Wi-Fi and the Bluetooth. The absence of mathematical models that takes into account all the parameters that affect the characteristics of these antennas present a difficulty in the design of this type of antennas. In this paper, our main contribution is the development of a synthesis and analysis model for PIFA antenna based on the artificial neural network method. For this reasons, we have developed a model of the neural network based on the multilayer perceptron to predict the resonance frequency and the bandwidth of a single band PIFA antenna. By applying the same method, we managed to find a multilayer perceptron structure that can accurately predict the dimensions of the PIFA single band antenna. Using the HFSS software, we designed the single band PIFA antenna that can operate at the frequency 2.45 GHz and presents a bandwidth at -10dB equal 1.0552 GHz, a good reflection coefficient (-51 dB), the gain is 6.5867 dB.

Keywords: PIFA, Neural Networks MLP, Prediction, Modeling, Antenna, Bandwidth.

1 Introduction

Most used antennas for mobile phones are monopolies [1]. With the development of new standards and design constraints, the makers of mobile phone prefer today's integrated antennas. Owing to their advantages of low profile, light weight, easy fabrication and good performance make printed inverted F antennas (PIFAs) one of the most popular antennas in today's wireless communication handset [2–5]. A PIFA operates at a resonant length of $\frac{\lambda}{4}$, it is highly conducive to a small and lightweight design and suitable for use as an internal antenna. There are several methods that have been proposed by previous papers to design a PIFA antenna. Earlier conventional analytical, numerical and optimization techniques were used to design and analyze the performance of antennas. However, these conventional techniques require high computational efforts which make them complicated and time consuming. Simulation methods duplicate the same process even if a small change is done in the geometry, which also require lots of patience and time.

Artificial Neural Network (ANN) models have been recently used efficiently in the design of antennas, circuits and microwave devices due to their ability to be an efficient alternative to conventional methods such as analytical methods, or numerical modeling method to model any arbitrary nonlinear input–output relationships between different data sets giving [6]. ANN is a computational model inspired by networks of biological neurons, that was developed to model nonlinear problems by employing a mathematical model and by imitating data processing technique of human brain's structure [7]. In the literature, ANNs models were used for the analysis of microstrip antennas. In [8] the authors has applied the ANN model to determinate the antenna dimensions and the bandwidth of a rectangular patch. In [9] ANN models were applied to predict the notch band frequency of an ultra-wideband antenna. ANN models were used to calculate the resonance frequency of the rectangular patch antenna in [?, 11, 14]. In [12, 13] the dimensions of a rectangular microstrip patch antenna was determined by applying the ANNs method. ANN models have been also used in many design of PIFA antenna to compute the resonance frequency and to minimize the size by calculating the lengths and widths the slots [15]. However, the ANN model is limited to the study of the resonance frequency of the PIFA antenna [16, 17].

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In this work, we are interested to design a PIFA antenna that can operate at the resonance frequency of 2.45 GHz for wireless application, Wi-Fi, Bluetooth and ISM band by applying an ANN model based on MLP structure. We are interested at first time to predict the resonance frequency and the bandwidth of the single band PIFA antenna. In the second time, we develop a neural network model based on the MLP to predict the dimensions of the PIFA antenna.

The paper is organized as follows. PIFA antenna theory is presented in Section 2, while Section 3 provides a theoretical description of the artificial neural network. A description of the proposed method used to predict the resonance frequency and the bandwidth, along with an explanation of the performance in terms of the regression coefficient, MSE, MAE and R_{error} and graphical plotting tools, are provided in section 4 and 5. Finally, Section 6 shows our conclusions.

2 PIFA antenna theory

The inverted-F antenna is evolved from a quarter wavelength monopole antenna. It is basically a modification of the inverted F antenna IFA which is consisting of a short vertical monopole wire.

To increase the bandwidth of the IFA a modification is made by replacing the wires with a horizontal plate and a vertical short circuit plate to obtain a PIFA antenna. PIFA is suitable to indoor wireless environment because of high gain in both vertical and horizontal states of polarization as well as any other area.

The conventional PIFA is constituted by a top patch, a shorting plate and a feeding plate. The top patch is mounted above the ground plane, which is connected also to the shorting plate and the feeding plate at proper positions (Figure 1). They have the same length as the distance between the top patch and the ground plane. The standard design formula for a PIFA antenna is given by [18,19]:

$$f_r = \frac{c}{4.(L_p + W_p)} \quad (1)$$

Where:

- f_r is the resonant frequency of the main mode;
- c is the speed of light in the free space;
- W_p and L_p are the width and the length of the radiating plate, respectively.

Fig. 1 Geometry of the PIFA antenna

3 Artificial neural network

In the formative years of artificial neural networks (1943–1958), several researchers stand out for their pioneering contributions:

- McCulloch and Pitts (1943) for introducing the idea of neural networks as computing machines.
- Hebb (1949) for postulating the first rule for self-organized learning.
- Rosenblatt (1958) for proposing the perceptron as the first model for learning with a teacher (supervised learning).

Rosenblatt's perceptron and least-mean-square (LMS) algorithm (developed by Widrow and Hoff 1960) are basically a single-layer neural network. These networks are limited to the classification of linearly separable patterns. To overcome the practical limitations of the perceptron and the LMS algorithm, we look to a neural network structure known as the multilayer perceptron .

Figure 2 shows the architectural graph of a multilayers perceptron (MLP) with two hidden layers and an output layer. To set the stage for a description of the MLP in its general form, the network shown here is fully connected (Figure 2). This means that a neuron in any layer of the network is connected to all the

neurons (nodes) in the previous layer. Signal flow through the network progresses in a forward direction, from left to right and on a layer-by-layer basis [20].

Fig. 2 Architectural graph of a multilayers perceptron with two hidden layers.

4 Prediction of the resonance frequency and bandwidth of a single band PIFA antenna

The used ANN model to predict the resonance frequency and bandwidth of a single band PIFA antenna is described in figure 3. The inputs of our network are the width of radiating plane W_p , the length of radiating plane L_p , the width of ground plane W_g , the length of ground plane L_g , the distance between the shorting plate and the feeding plate F_s , the width of feeding plate W_f and the width of shorting plate W_s . The output of the network is the resonance frequency f_r and the antenna bandwidth which can be calculated by predicting the lower and upper frequency (f_1, f_2) at -10 dB respectively. The bandwidth is given by the flowing equation:

$$Bd = f_2 - f_1 \quad (2)$$

Where:

- f_2 and f_1 are respectively the lower and upper frequency at -10 dB;
- Bd is the antenna bandwidth.

Fig. 3 MLP structure used to predict the bandwidth and resonance frequency of the PIFA single band antenna

Our goal in this part is to apply the ANN model based on the MLP for predicting the resonance frequency and the antenna bandwidth. To build ANN structure, we have to determine: the number of layers, the number of neurons in each layer, the activation function and the learning algorithm.

4.1 Results and discussions

For training the MLP model, we built using the HFSS software a database of 129 inputs-outputs, the adopted method is based on the variation of the parameters of the PIFA antenna and the filling each time the matrices of the input-output. To train the network, we have to divide the database in training, validating and testing phases. Several tests are carried out and the distribution which gives the good results is presented on the table below:

Table 1 Database distribution

Phase	Number of Samples	Percentage
Training	91	70 %
Validation	19	15%
Test	19	15%

The MLP network is trained with various learning algorithms, Gradient (G), Gradient with momentum (GM), Resilient Backpropagation (RP), One step secant (OSS) and Levenberg-Marquardt (LM), in order to find the best algorithm and to reduce the error between the network output and the targuet. The performance of each algorithm is evaluated by calculating the Mean Square Error (MSE), Relative Error R_{error} and MAE Mean Absolute Error. These criteria are defined by the following equations:

$$MSE = \frac{1}{N} \sum_{i=1}^{i=N} (y_i - \hat{y}_i)^2 \quad (3)$$

$$R_{error} = E\left[\frac{(y_i - \hat{y}_i)^{\frac{1}{2}}}{y_i^2}\right]^{\frac{1}{2}} \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{i=N} |y_i - \hat{y}_i| \quad (5)$$

Where y_i and $\hat{y}_i$ are respectively the target and the network output.

The obtained results show that the training algorithm of Levenberg Marquardt (LM) presents the lowest MSE , MAE , and R_{error} values. It is therefore the most suitable for our model (table 2).

Table 2 Values of MSE , MAE et R_{error} for different training algorithm

Training Algorithm	MSE	MAE	R_{error}
G	0.4580	0.5178	0.4122
GM	0.3731	0.4364	0.3358
OSS	0.0254	0.1385	0.0289
RP	0.0175	0.0600	0.0074
LM	0.0042	0.0378	0.0038

To determine the appropriate transfer function for the hidden layer of our network, we used the same method adopted to choose the learning algorithm. Using MSE , MAE and R_{error} as network performance criteria, the obtained results show that the hyperbolic tangent sigmoid (tansig) function is more appropriate for our MLP model because it has MSE , MAE and R_{error} the lowest, the table 3 shows the obtained results.

Table 3 Values of MSE , MAE et R_{error} for different training function

Transfer Function	MSE	MAE	R_{error}
hardlim	0.2214	0.3437	0.1993
purelin	0.0157	0.0816	0.0141
satlin	0.0067	0.0469	0.0060
logsig	0.0078	0.0571	0.0070
tansig	0.0042	0.0378	0.0038

We followed the same method for determining the number of hidden layers and the number of neurons in each layer. The tables 4 and 5 below summarize the obtained results.

Table 4 Values of MSE , MAE et R_{error} for different number of hidden layers

number of hidden layers	MSE	MAE	R_{error}
1	0.0042	0.0378	0.0038
2	0.0502	0.1486	0.0452
5	0.0997	0.1876	0.0897
10	0.02561	0.0916	0.0230

Table 5 Values of MSE , MAE et R_{error} for different number of neurons in hidden layer

Number of neurons	MSE	MAE	R_{error}
5	0.0085	0.0587	0.0077
10	0.0042	0.0378	0.0038
15	0.0095	0.0645	0.0086
20	0.0098	0.0643	0.0088
30	0.0271	0.1220	0.0244

From the tables above the good results are obtained for a single hidden layer with 10 neurons. The final structure of our model and its different parameters are shown in the table 6.

Table 6 MLP final structure

ANN parameters	
Number of samples	129
Training algorithm	Levenberg-Marquard
Transfer function	Tangent Sigmoid
Network structure	7-10-3

We present in the figure 4 the convergence of the learning algorithm (Levenberg-Marquardt) during the phases of learning, validation, and the test phase. The performance of the network is evaluated using the mean squared error (MSE) as a criterion. More MSE is close to zero more the result is better. It is clear from these results that the training phase is performed in 17 iterations.

Fig. 4 Convergence of the learning algorithm (LM)

To check the structure of our network, the test procedure is performed by taking 19 distinct input data samples not included in the database used for training. The resonance frequency of the antenna and the bandwidth (the maximum and minimum frequency at -10 dB) calculated by the network outputs are compared to the obtained resonance frequency and the bandwidth using HFSS software. The results of the comparison are presented in the tables below:

Table 7 Comparison between $f_{r_{HFSS}}$, $f_{l_{HFSS}}$, $f_{u_{HFSS}}$ obtained by the HFSS software and $f_{r_{ANN}}$, $f_{l_{ANN}}$, $f_{u_{ANN}}$ estimated by ANN model

f_r (HFSS)	f_l (HFSS)	f_u (HFSS)	f_r (ANN)	f_l (ANN)	f_u (ANN)
2.4628	2.2116	2.7391	2,32008	2,76523	2,504044
2.5382	2.2663	2.8191	2,32905	2,79002	2,522255
2.5678	2.2764	2.5678	2,33364	2,83564	2,558067
2.6080	2.3266	2.9095	2,32994	2,85663	2,575573
2.6181	2.3367	2.9397	2,32384	2,87692	2,592727
2.6281	2.3367	2.9397	2,31716	2,89708	2,609468
2.6583	2.3668	2.9799	2,31166	2,91772	2,625755
2.6482	2.3568	2.9698	2,30856	2,93925	2,641592
2.7035	2.4020	3.0201	2,30837	2,96185	2,657023
2.7035	2.4120	3.0352	2,31261	2,99513	2,678085
2.6884	2.3869	3.0201	2,31568	3,00985	2,686960
2.7186	2.4171	3.0503	2,32183	3,03469	2,701589
2.7337	2.4322	3.0653	2,33536	3,08416	2,73021
2.4322	2.1608	2.6884	2,26470	2,69112	2,450965

To confirm the efficiency of our developed model, we present in figure 5, 6 and 7 the resonance frequency and the lower and the upper frequency at -10 dB respectively according to the number of samples in the database. It is very clear that the estimated results using the ANN based on the MLP are very close to the obtained results using HFSS software.

Fig. 5 Comparison between f_r (HFSS) and f_r (ANN)

Fig. 6 Comparison between $f_1(\text{HFSS})$ and $f_1(\text{ANN})$

Fig. 7 Comparison between $f_2(\text{HFSS})$ and $f_2(\text{ANN})$

To reinforce the obtained results, a calculation of the regression coefficient R is performed. It describes the relationship between the predicted values (results) and the desired values (targets). The obtained results are illustrated in figure 8 for each case. The data should fall along a straight line with a 45 degree, for a perfect fit, where the outputs of the network are equal to the desired outputs. For this problem, the fit is reasonably good for all data sets with the value of R being approximately equal to 1 in each case. The value of this coefficient shows that the network built with the structure (7-10-3) is efficient.

Fig. 8 Regression coefficient of trained ANN

5 Prediction the dimensions of the PIFA antenna

The artificial neural network model used to predict the dimensions of the PIFA single band antenna is shown in Figure 9. The inputs of our network in this case are the resonant frequency f_r , the distance between the shorting plate and the feeding plate F_s and the shorting plate width W_s . The network outputs are the width of the radiating plate W_p , the length of the radiating plate L_p , the width of the ground plane W_g , the length of the ground plane L_g and the width of the feeding plate W_f .

Fig. 9 MLP structure used to predict the dimensions of the PIFA single band antenna

5.1 Results and discussions

The prediction of PIFA antenna dimensions requires the determination of a neural network model that accurately modeling the existing relationship between inputs and outputs. For this, we followed the same method adopted to predict the resonance frequency and the bandwidth in order to find the network structure. The appropriate training algorithm, the number of hidden layers, the number of neurons in each layer and the appropriate activation function. The table 8 presents the structure of the network and its various parameters.

Table 8 MLP final structure

ANN parameters	
Number of samples	86
Training algorithm	Levenberg-Marquard
Transfer function	Tangent Sigmoid
Network structure	3-14-10-5

In this case, the distribution that gives the good results is shown in the table 9.

Table 9 Database distribution

Phase	Number of Samples	Percentage
Training	52	60 %
Validation	9	10%
Test	26	30%

The convergence of the learning algorithm (Levenberg-Marquardt) during the training, the validation, and the test phases is illustrated in Figure 10. The performance of the network is evaluated using the mean squared error (MSE) as a criterion. It is clear from these results that the learning phase performs well at 23 iterations.

Fig. 10 Convergence of the training algorithm (LM)

To verify the structure of our network, we present in the following figures (11, 12, 13, 14, 15) a comparison between the obtained dimensions using HFSS software and those predicted by our neural network. It is very clear that the obtained results by the neural network based on the multilayers perceptron are very close to the obtained results using HFSS software.

Fig. 11 Comparison between $W_p(\text{HFSS})$ and $W_p(\text{ANN})$

Fig. 12 Comparison between $L_p(\text{HFSS})$ and $L_p(\text{ANN})$

Fig. 13 Comparison between $W_g(\text{HFSS})$ and $W_g(\text{ANN})$

Fig. 14 Comparison between $L_g(\text{HFSS})$ and $L_g(\text{ANN})$

Fig. 15 Comparison between $W_f(\text{HFSS})$ and $W_f(\text{ANN})$

We present in figure 16 the regression coefficient R for our MLP network. From this results the fit is reasonably good for all data sets with the value of R is approximately equal to 1 in each case, which shows that the ANN model with the structure (3-14-10-5) is powerful.

Fig. 16 Regression coefficient R

From these results, we conclude that the proposed ANN model is effective for predicting the optimal dimensions of the antenna that can resonate at the 2.45 GHz frequency. These dimensions are simulated using HFSS software. The obtained antenna has a reflection coefficient equal to -51.0614 dB . Table 10 shows the obtained dimensions by the ANN model with $F_s = 20 \text{ mm}$ and $W_s = 1.7 \text{ mm}$.

Table 10 Dimensions in *mm* of the PIFA antenna obtained by ANN

$W_p(ANN)$	$L_p(ANN)$	$W_g(ANN)$	$L_g(ANN)$	$W_f(ANN)$
40.0161	11.67132	39.9585	51.9874	5.94257

Figure 17 illustrates the reflection coefficient S_{11} of the designed antenna.

Fig. 17 Reflection coefficient of the PIFA obtained PIFA antenna by ANN

We present in the figure 18 the 3D radiation pattern of this antenna at the frequency 2.45 *GHz*. This diagram shows the total radiation power.

Fig. 18 3D radiation pattern for the obtained PIFA antenna by ANN for $f_r=2.45$ *GHz*

From this results, the obtained PIFA antenna by ANN has an Omni-directional pattern with a maximum gain of about 6,5867 dB for 2,45 GHz.

We present in the following figures the input impedance Z_{in} and the standing wave ratio VSWR of the obtained PIFA antenna by ANN. More the input impedance Z_{in} tends to characteristic impedance of the transmission line Z_0 more the antenna is adapted, a good adaptation is also for the VSWR between 1 and 2 ($1 < VSWR < 2$).

Fig. 19 Evolution of the input impedance of the obtained PIFA antenna by ANN

Fig. 20 Evolution of the standing wave ratio of the obtained PIFA antenna by ANN

We remark that the real and the imaginary components of the impedance remain about 50 Ω and about zero Ω , respectively throughout the antenna bandwidth between the frequencies 1.6935 GHz up to 2.7487 GHz (figure 19). We also observe that the standing wave ratio of the obtained PIFA antenna by ANN is approximately 1.034 throughout the bandwidth of our antenna.

In this section, our goal is to apply the ANN method based on the MLP structure for the prediction of the best dimensions of the antenna which gives the good performances for the antenna, such as the size, the bandwidth, the gain and the VSWR. The comparison between the proposed antenna using ANN method and the antennas cited in the literature in terms of the bandwidth, the gain and the reflection coefficient S_{11} is listed in Table

	Antenna type	$f_r(GHz)$	$BW(MHz)$	$S_{11}[dB]$	$Gain[dB]$
This paper		2.45	1055.2	-51	6.5867
[21]	PIFA mono-bande	2.478	400	-43	2.9
[22]	PIFA tri-bandes	2.4	300	-25	5.482
[23]	Parallel Dual-slot PIFA	2.45	320	-42	6.41

6 Conclusion

In this paper, we are interested to apply the artificial neural networks method based on the multilayer perceptrons (MLP) to estimate the values of the resonant frequency, the antenna bandwidth and the antenna dimensions. To prove the performance of the obtained ANN model, we predict the resonance frequency and bandwidth of the PIFA antenna that can operate in the ISM band (application in the medical field, mobile phones, Wi-Fi, Bluetooth) as well as its dimensions. The obtained results show that the artificial neural network technique is an efficient method for antenna design. It gives the desired results with great precision in a very short time. It takes into account all the parameters that affect the characteristics of the antennas. The neural network method can also be applied to all types of antennas.

Conflict of interest

The authors declare that they have no conflict of interest.

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Figures

Figure 1

Geometry of the PIFA antenna

Figure 2

Architectural graph of a multilayers perceptron with two hidden layers.

Figure 3

MLP structure used to predict the bandwidth and resonance frequency of the PIFA single band antenna

Figure 4

Convergence of the learning algorithm (LM)

Figure 5

Comparison between fr(HFSS) and fr(ANN)

Figure 6

Comparison between $f_1(\text{HFSS})$ and $f_1(\text{ANN})$

Figure 7

Comparison between $f_2(\text{HFSS})$ and $f_2(\text{ANN})$

Figure 8

Regression coefficient of trained ANN

Figure 9

MLP structure used to predict the dimensions of the PIFA single band antenna

Figure 10

Convergence of the training algorithm (LM)

Figure 11

Comparison between Wp(HFSS) and Wp(ANN)

Figure 12

Comparison between Lp(HFSS) and Lp(ANN)

Figure 13

Comparison between Wg(HFSS) and Wg(ANN)

Figure 14

Comparison between Lg(HFSS) and Lg(ANN)

Figure 15

Comparison between Wf (HFSS) and Wf (ANN)

Figure 16

Regression coefficient R

Figure 17

Reflection coefficient of the PIFA obtained PIFA antenna by ANN

Figure 18

3D radiation pattern for the obtained PIFA antenna by ANN for fr=2.45 GHz

Figure 19

Evolution of the input impedance of the obtained PIFA antenna by ANN

Figure 20

Evolution of the standing wave ratio of the obtained PIFA antenna by ANN