Arab J Sci Eng (2016) 41:3231–3238
DOI 10.1007/s13369-016-2140-4

RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Bandwidth and Mutual Coupling Analysis of a Circular Microstrip MIMO Antenna Using Artificial Neural Networks

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Received: 31 October 2014 / Accepted: 14 April 2016 / Published online: 9 May 2016

Abstract A ground plane reduced circular microstrip antenna resonating at multiband of frequencies 3.5, 5.2, 6.3 and 8.4 GHz is developed. The proposed antenna gives a wide impedance bandwidth of 75 % in the frequency range 3.2 to 7 GHz, covering a part of the UWB operating frequency range. The antenna is coaxially fed, supported by a rectangular strip above the ground plane. The effect of strip width on the variation in impedance bandwidth of the proposed antenna is studied using artificial neural networks, and a comparative study is made. A 2×2 multiple input multiple output system is designed using the developed antenna, and the mutual coupling of the proposed antenna system is analyzed for various separations and frequencies by using artificial neural networks.

Keywords Artificial neural networks · Circular microstrip antenna · Impedance bandwidth · MIMO systems · Mutual coupling

1 Introduction

In everyday life, the communication technology plays vital role in different areas such as medical, military domains, civil, sport wear and wildlife study. The emerging developments in wireless communications and recent advancements in antenna technology have given the ample opportunity to the researchers. The microstrip antennas are vital in many wireless communication systems such as WiFi, WLAN and mobile, due to their smaller size, ease of fabrication and low cost.

However, their performance is limited due to narrow bandwidth. In the literature, many techniques are discussed to improve the impedance bandwidth of microstrip patch antennas. The reduction in ground plane to improve the impedance bandwidth of these microstrip antennas is discussed in [1–3].

MIMO technology plays important role in achieving larger data rates and higher throughputs in the present wireless communication scenario. For first time in the history of wireless communications, the pioneer Foschini predicted that the multiple number of antennas at the transmission and reception side will improve the data rates, without increase in additional power and transmission bandwidth [4]. Since then, various researchers have contributed for the growth of the MIMO technology. When MIMO technology is used for various communication devices such as mobile phone, personal digital assistants and laptop, mutual coupling comes into picture. The main reason for this is the close spacing of the multiple antennas in such volume restricted devices. The main sources of this mutual coupling are studied in [5,6], and the effect of mutual coupling on the channel capacity of the MIMO systems is discussed in [7]. Though, in the literature numerous techniques are proposed to reduce this mutual coupling [8–10], and less importance is given to study the effect of antenna separation on the mutual coupling. In the present work, artificial neural networks (ANNs) are used to analyze this problem.

The nonlinear problems of microwave devices, circuits and antennas can be easily solved using the computational tool, artificial neural networks (ANNs) [11]. Artificial neural networks find numerous applications in thrusting areas such as RF circuit design, control, biomedical engineering, pattern recognition, and speech processing. ANNs are popularly

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used for modeling and designing microstrip antennas. In [12], the slot shape and size of microstrip antenna for improving the antenna performance are presented. Similarly in [13], the dimensions of the patch antenna are optimized for X/Ku band using ANNs. Usually, the data for training a neural network are taken from an EM simulator or calculated mathematically or measured in the laboratories. Once the ANN structure is properly trained with proper weights, it can be used for analyzing the given However, the ANNs once properly trained can handle any number of parameters for any range of values [14].

In the present paper, a wideband circular microstrip antenna resonating at multiband of frequencies 3.5, 5.2, 6.3 and 8.4 GHz is developed. The antenna is formed on a reduced ground plane, where a rectangular strip is connected to the circular patch supporting the coaxial feed. The effect of width of the strip on the bandwidth of the proposed antenna is analyzed using artificial neural networks (ANNs), and an impedance bandwidth of 75 % is observed in the range 3.2–7 GHz. Also, a 2 × 2 MIMO system is formed using the proposed antenna, and the isolation between the two antennas is studied by changing the distance between antennas using artificial neural networks.

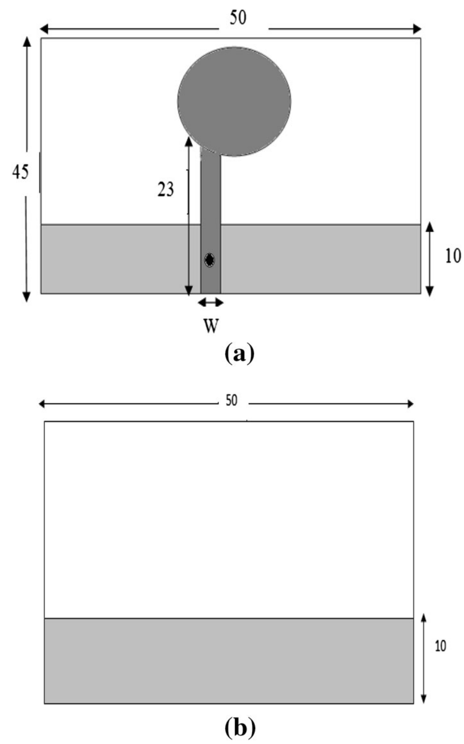


Fig. 1 Proposed circular microstrip antenna. **a** Top view, **b** bottom view

2 Antenna Design

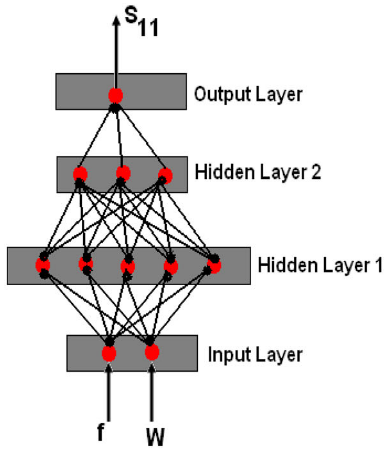
A circular microstrip antenna of size $50 \times 45\,\text{mm}^2$ is formed on a substrate of thickness 1.6 mm as shown in Fig. 1a. The radius of the circular patch is taken as 15 mm and a rectangular strip of length 23 mm is attached to the patch and permittivity of substrate is taken as $\varepsilon_r = 4.3$. A normal rectangular microstrip antenna gives the bandwidth only in the range of 3–5 %, and its bandwidth can be enhanced by reducing ground plane. This is due to the generation of multiple resonant frequencies with the reduction in ground plane. All the generated resonant frequencies couple each other, resulting in improved impedance bandwidth [15].

The ground plane of the proposed antenna is reduced gradually, its resonant behavior is studied for different values and at the reduction of 10 mm it was observed to give good resonant behavior. Hence, the antenna is designed for a ground plane area of $50 \times 10\,\text{mm}^2$ as shown in Fig. 1b. The bandwidth analysis of the proposed antenna is performed with the help of the computational tool artificial neural networks, as they give accurate results once trained properly.

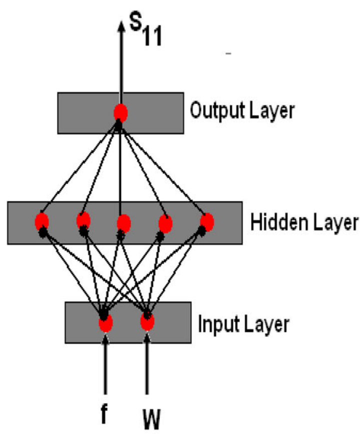
The return loss of the proposed antenna is obtained by varying the width '*W*' of the strip in the range 3 to 10 mm, with the help of 6000 samples of data, which are used for training and testing process. As the return loss characteristics are nonlinear in nature, the ANNs can be used effectively for predicting the future values. The neural networks are trained with a learning rate of 0.25 for 1000 epochs. For the present work, the multilayer perceptron feed-forward back-propagation (MLPFFBP) and radial basis function (RBF) neural structures are used to train the neural model, which are shown in Fig. 2a, b, respectively.

MLPFFBP structures are supervised networks, and weights of the neural structure are adjusted using back-propagation algorithm. Typically, the MLP layers are organized as a set of interconnected layers of artificial neurons, input, hidden and output layers. When the structure is provided with data through the input layer, the neurons in this layer propagate the weighted data and randomly selected bias through the hidden layers. Once the net sum at a hidden node is determined, an output response is provided at the node using a transfer function. Two important characteristics of the MLP are its nonlinear processing elements which have a nonlinear activation function that must be smooth and its massive interconnectivity.

RBF structures are feed-forward networks with one hidden layer, and they can be trained using supervised or unsupervised learning. The RBF, which is multilayer and feed-forward, is often used for strict interpolation in multidimensional space. The input layer is composed of input data, and the hidden layer transforms the data from the input space to the hidden space using a nonlinear function. The output layer, which is linear, yields the response of the network. The argument of the activation function of each hidden unit in an RBF network computes the Euclidean distance between the



(a)



(b)

Fig. 2 Neural structures of **a** MLPFFBP, **b** RBF

input vector and the center of that unit. In the structure of RBF network, the input data, x, are a p-dimensional vector, which is transmitted to each hidden unit. The activation function of hidden units is symmetric in the input space, and the output of each hidden unit depends only on the radial distance between the input vector, x, and the center for the hidden unit. In the present case, the inputs to the neural structure are frequency 'f', strip width 'W' and output is S-Parameter S_{11}.

During the training process, different weights of the neural structure are adjusted to reduce the error between the target output and required output of the ANN. The neural model is trained with different learning algorithms namely conjugate gradient (CG), quasi-Newton MLP (QN-MLP), quasi-Newton(QN), Huber-quasi-Newton (HQN), adaptive back-propagation (ABP), simplex method (SM) and sparse training (ST). The brief introduction of these algorithms is presented below.

Conjugate gradient (CG) This basic back-propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). In this algorithm, a search is performed along of correlation coefficient, and hence, it is used for studying the effect of width 'W' variation on bandwidth of the antenna. From Table 1, it can also be observed that MLPFFBP neural structure is shown to give high correlation coefficient compared to RBF neural structure. The quasi-Newton algorithm is an advanced training algorithm, which utilizes second-order derivative information [16]. The S-Parameters of the antenna exhibit highly nonlinear conjugate directions, which produces generally faster convergence than steepest descent directions.

Quasi-Newton and quasi-Newton MLP These Newton's method often converges faster than conjugate gradient methods. However, it is complex and expensive to compute the Hessian matrix for feed-forward neural networks. In optimization, quasi-Newton methods find local maxima and minima of functions. Quasi-Newton methods are based on Newton's method to find the stationary point of a function, where the gradient is 0.

Adaptive back-propagation (ABP) The adaptive back-propagation (ABP) training algorithm is a renowned representative of all iterative gradient descent algorithms used for supervised learning in neural networks. It is designed to minimize the mean square error (MSE) between the actual output of a multilayer feed-forward neural network and the desired output. BP has a great high merit of simplicity on implementation and calculation compared to other mathematically complex techniques.

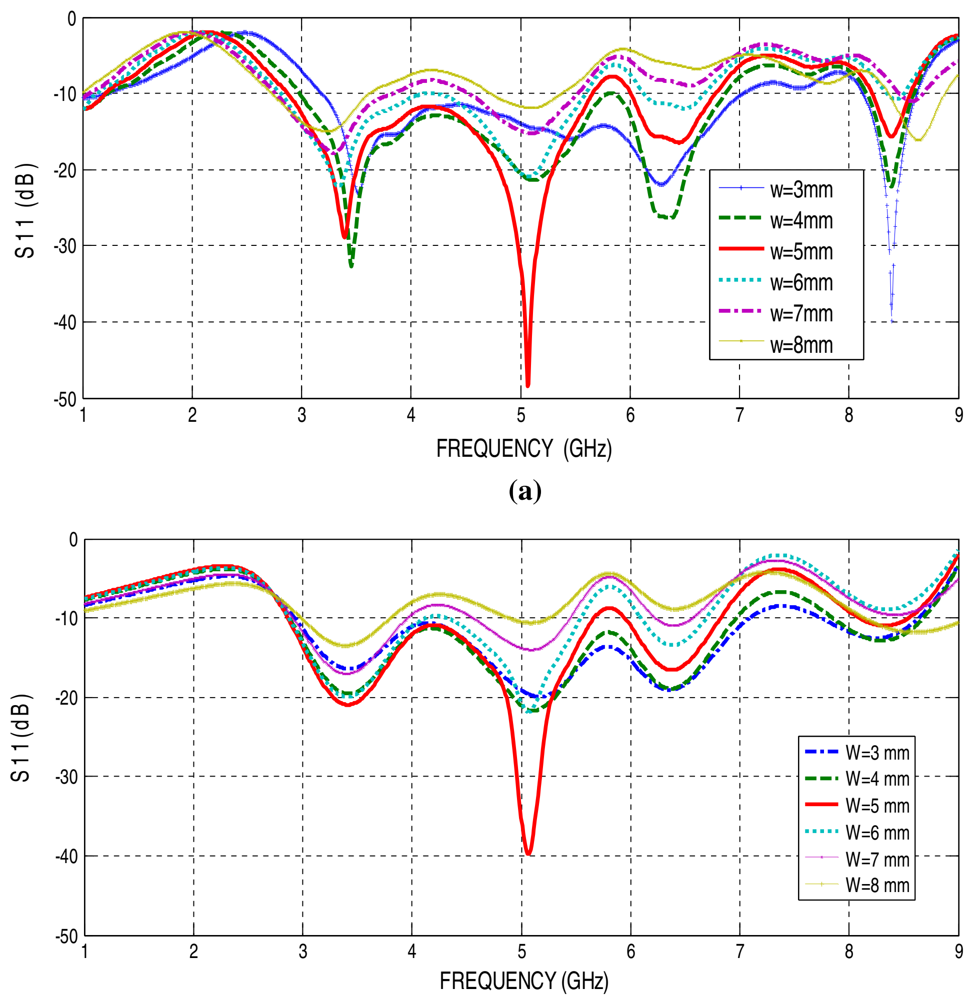
Simplex method The simplex algorithm operates on linear programs in standard form. The solution of a linear program is accomplished in two steps. In the first step, known as Phase I, a starting extreme point is found. Depending on the nature of the program, this may be trivial. The possible results of Phase I are either a basic feasible solution is found or that the feasible region is empty. In the latter case, the linear program is called *infeasible*. In the second step, Phase II, the simplex algorithm is applied using the basic feasible solution found in Phase I as a starting point. The possible results from Phase II are either an optimum basic feasible solution or an infinite edge on which the objective function is unbounded.

Using MLPFFBP and RBF neural structures, the above-mentioned algorithms are trained and tested, and for each algorithm, the training and testing errors are shown in Table 1. Here, quasi-Newton algorithm is shown to give reduced error with higher values nature where quasi-Newton algorithm succeeded in giving better performance compared to other algorithms owing to its ability of finding local maxima and minima using a second derivative function to predict the future values.

The reflection coefficient generated using MLPFFBP and RBF neural structures for different values of width 'W' are

Table 1 Comparison of training and testing errors with various algorithms for width variation analysis

Algorithm	Training error	Testing			Training error	Testing		
	Multilayer perceptron (MLP)				Radial basis function (RBF)			
		% Avg. error	% Max. Error	Corr. Coeff.		% Avg. Error	% Max. Error	Corr. Coeff.
ABP	0.04949	5.24250	66.6342	0.94731	0.05255	5.5708	53.8660	0.947960
CG	0.04946	5.25232	66.4733	0.94730	0.05248	5.5708	53.8660	0.947960
QN-MLP	0.03661	1.07334	23.17811	0.96752	–			
QN	0.00985	4.08445	53.18011	0.998042	0.036045	3.5680	29.9423	0.9811371
HQN	0.03663	4.08445	53.18011	0.968042	0.049446	5.3320	54.1282	0.945692
ST	0.05209	5.3510	67.60173	0.946648	–			
SM	0.04958	5.2703	66.4118	0.94731	0.05230	5.5035	53.1198	0.948926



(b)

Fig. 3 Variation in reflection coefficient for different values of strip width '*W*' using **a** MLPFFBP neural structure, **b** RBF neural structure

shown in Fig. 3. These characteristics are helpful in evaluating the impedance bandwidth of the antenna, which can be calculated using Eq. (1).

$$\%\mathrm{BW} = f_{\mathrm{H}} - f_{\mathrm{L}}/2(f_{\mathrm{H}} + f_{\mathrm{L}}) \quad (1)$$

The neurally generated and simulated impedance bandwidths at 10 dB return loss are calculated and compared as shown in Table 2. These bandwidths are calculated from the *S*-Parameters generated from Fig. 3 and are evaluated using Eq. (1). The values in Table 2, indicate that for a strip width of

Table 2 Comparison of simulated and ANN calculated bandwidth

S. No.	Width *W* (mm)	% of bandwidth simulated	% of bandwidth MLPFFBP	% of error	% of bandwidth RBF	% of error
1	3	74.94	73.58	1.8	82.2	8.8
2	4	66	63	4.5	67.8	2.6
3	5	64.9	65	0.15	65.4	0.7
4	6	38.1	38	0.262	35.5	6.8
5	7	30.7	29.2	4.8	30.3	1.3
6	8	28.12	27.3	2.9	26.5	5.7

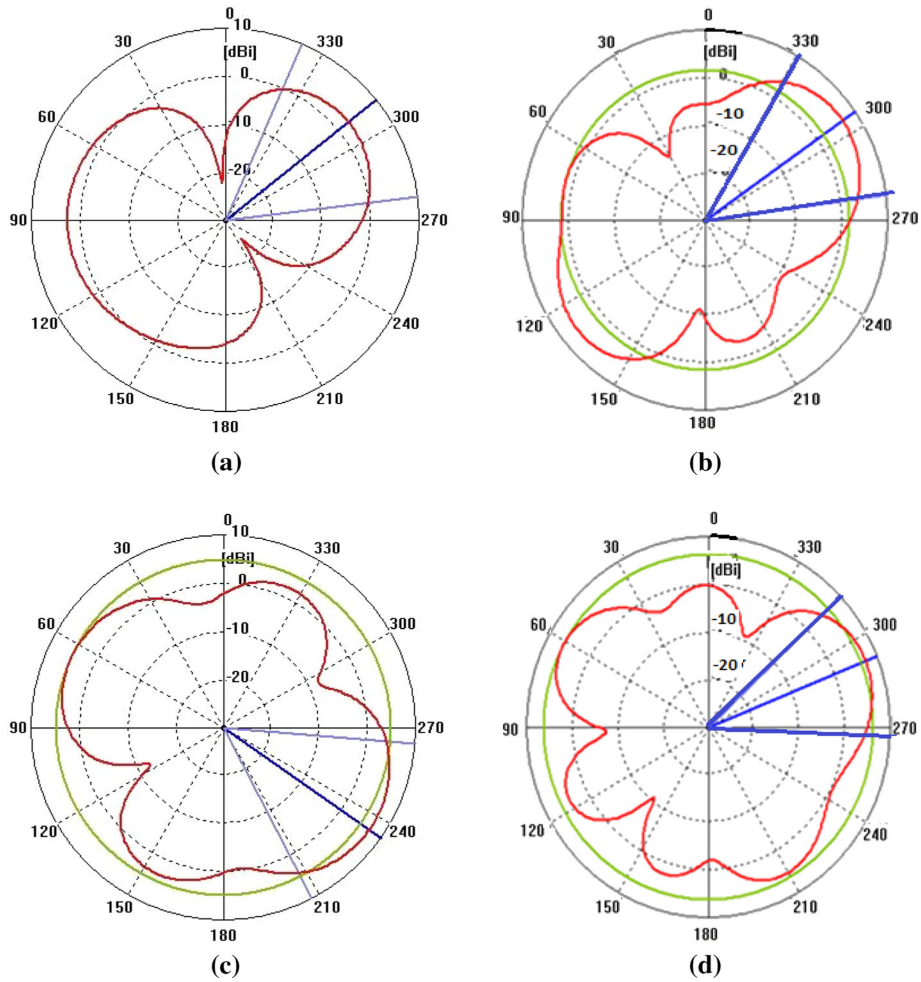


Fig. 4 Radiation patterns of the proposed antenna at the resonant frequencies.**a** 3.5 GHz, **b** 5.2 GHz, **c** 6.3 GHz, **d** 8.4 GHz

'*W*' = 3 mm, a maximum bandwidth of 74.94 % is obtained in the frequency range 3.2 to 7 GHz and the bandwidth reduces with the increase in strip width. Also, it can be observed that MLPFFBP structure gives a maximum error of 4.8 % and RBF structure gives a maximum error of 8.8 %, compared to the simulated bandwidth. The radiation patterns of the developed antenna at the resonant frequencies 3.5, 5.2, 6.3 and 8.4 GHz are shown in Fig. 4. From the radiation patterns, it can be observed that at higher resonant frequencies 5.2, 6.3 and 8.4 GHz, the antenna is shown to exhibit nearly omnidirectional characteristics. At 3.5 GHz, the main lobe is directed at 310° with a 3 dB angular beam width of 60°, at 5.2 GHz, the main lobe is directed at 305° with a 3 dB angular beam width of 55°, at 6.3 GHz, the main lobe is directed at 236° with a 3 dB angular beam width of 58°, and at 8.4 GHz, the main lobe is directed at 293° with a 3 dB angular beam width of 47°.

3 Mutual Coupling Analysis in MIMO Array Using ANNs

Nowadays, MIMO systems gained popularity as they offer huge data rates due to the multiple antennas employed. However, due to the close spacing between the antennas in small handheld devices such as mobile, PDAs and laptop, mutual coupling comes into picture. Usually, this mutual coupling is more, when the distance between the antennas is less and vice versa. In the present work, the analysis of this mutual coupling w.r.t. the distance is carried out using ANN by considering a 2×2 MIMO system using the proposed antenna as shown in Fig. 5. This antenna system is formed by replicating the antenna shown in Fig. 1, separated by a distance 'd'. The mutual coupling is evaluated by giving feed to the first antenna with second antenna terminated to an impedance of $50\,\Omega$.

The amount of isolation between the antennas can be studied using S_{21}-parameter, which is highly nonlinear in nature. To predict the nonlinear nature of this parameter, ANNs can be effectively utilized. Any EM simulator can give the isolation between the antennas for a specific separation between the antennas only. However, once the ANNs are properly trained with a specific set of trained data, the mutual coupling can be calculated in very short times for any value of the separation between the antennas with more accuracy. Also, its dependence on the frequency can be estimated easily.

The data sets are generated from the simulation software FEKO, and nearly 6000 samples are taken. For training, 4000 samples are used and for testing 2000 samples are utilized. Here, the MLPFFBP structure is used for calculating the mutual coupling as it was observed to give more accurate results compared to other structures during the training process.

In this case also, the training and testing errors are evaluated using various algorithms for both MLPFFBP and RBF structures to analyze mutual coupling as mentioned in Table 3. Also, it can be observed that MLPFFBP neural structure is shown to give high correlation coefficient (*0.998336*) compared to RBF neural structure (*0.990786*), indicating its efficiency for evaluating *S*-Parameters of antennas. Due to the better performance of QN algorithm, it is used for modeling the mutual coupling for different values of separation between the antennas. The distance '*d*' between the two antennas is varied from 30 to 50 mm, and the variation in isolation with respect to distance is obtained using the neural network structure, which is shown in Fig. 6. The evaluated parameter S_{21} gives the amount of mutual coupling between the two antennas, and lesser the values of S_{21} better the isolation between the antennas. The main importance of using ANN is to study the variation in mutual coupling w.r.t. different operating frequencies. In Fig. 7, the variation in mutual coupling w.r.t distance for different frequency values is shown. These values are generated using ANN structure with more accuracy in very short time. The same values can

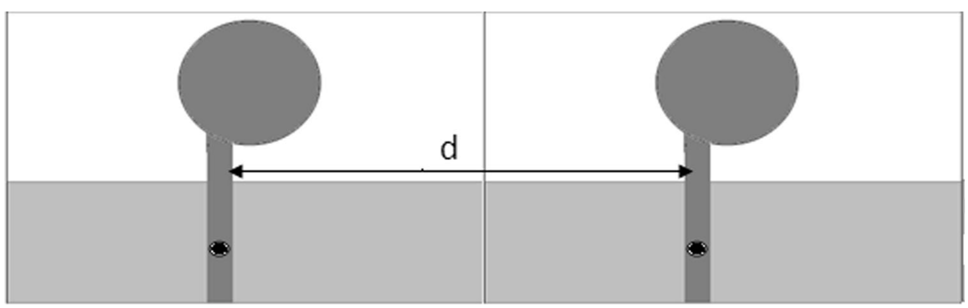


Fig. 5 Two element MIMO array using the proposed antenna

Table 3 Comparison of training and testing errors with various algorithms for mutual coupling analysis

Algorithm	Training error	Testing			Training error	Testing		
	Multilayer perceptron (MLP)				Radial basis function (RBF)			
		% Avg. error	Max. error	Corr. Coeff.		% Avg. error	% Max. error	Corr. Coeff.
ABP	0.03002	3.00585	48.418	0.998172	0.06971	7.2779	50.7548	0.990918
CG	0.02980	3.00585	48.418	0.998172	0.69887	7.2973	50.4506	0.990895
QN-MLP	0.02980	3.00625	48.415	0.998172	–			
QN	0.02641	2.718418	48.043	0.998336	0.067926	7.1405	53.10513	0.990786
HQN	0.02708	2.76181	46.860	0.998397	0.06960	7.2755	50.68015	0.990917
ST	0.06991	3.006253	48.415	0.9981726	–			
SM	0.02682	2.73269	47.149	0.998370	0.069266	7.2065	52.4173	0.990943

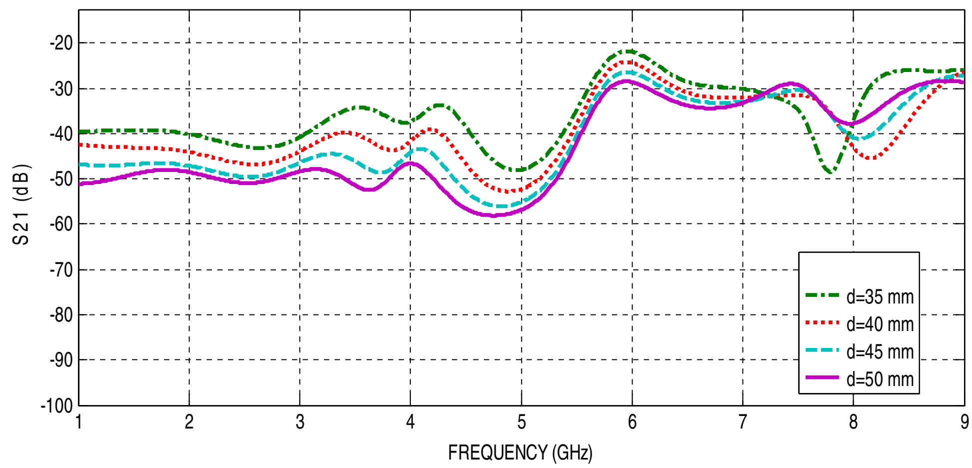


Fig. 6 ANN generated mutual coupling for different values of ‘d’

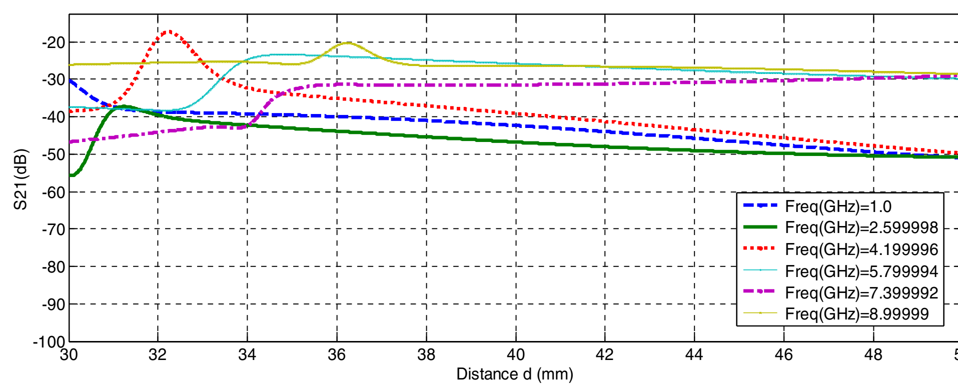


Fig. 7 ANN generated mutual coupling for different frequencies

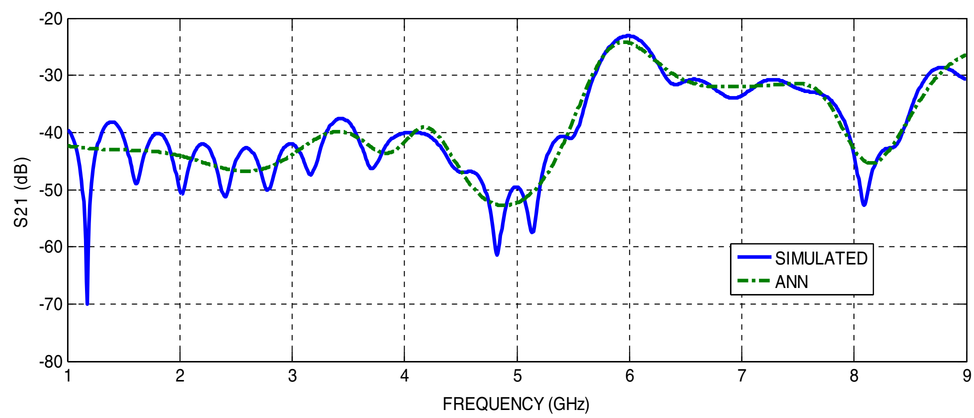


Fig. 8 Comparison between simulated and ANN generated mutual coupling for d = 40 mm

be generated using an EM simulator; however, taking more time and also the process is tedious and cumbersome.

In the present work, the beauty of ANN is to study the mutual coupling for different values of separation at different frequencies, more accurately at a faster rate. The comparison of mutual coupling with ANN and EM Simulator for an optimum separation of 40 mm is shown in Fig. 8. The ANN generated and simulated values almost resemble except at the sudden peaks giving a maximum variation of ± 6 dB. This variation is acceptable for most of the practical cases in evaluating the mutual coupling. Hence, ANN is a better choice for evaluating *S*-Parameters of antennas, where faster evaluation of the desired parameter is the main criteria.

The performance of a MIMO system can be better analyzed using envelope correlation coefficient parameter. The correlation coefficient depends on the *S*-Parameters of the developed MIMO system which is calculated using the Eq. (2). The correlation coefficient plot w.r.t frequency is shown in Fig. 9. The proposed antenna resonates at 3.5, 5.2, 6.3 and 8.4 GHz frequencies, and at these frequencies the

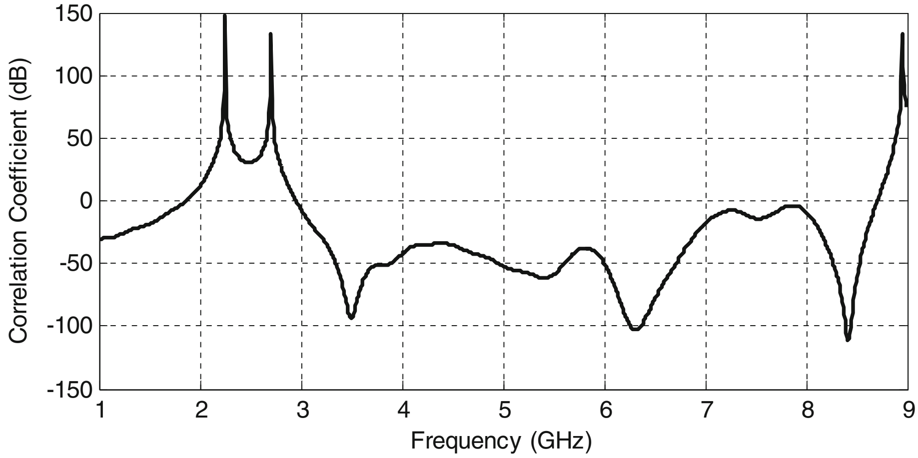


Fig. 9 Correlation coefficient of the proposed MIMO system

amount of correlation is observed to be very low, indicating the higher amount of isolation between the antennas.

$$\rho = \frac{\left|S_{11}^{*}S_{12} + S_{21}^{*}S_{22}\right|^{2}}{\left(1 - \left|S_{11}\right|^{2} - \left|S_{21}\right|^{2}\right)\left(1 - \left|S_{22}\right|^{2} - \left|S_{12}\right|^{2}\right)} \qquad (2)$$

where ρ represents the correlation coefficient.

4 Conclusions

A ground plane reduced circular microstrip antenna resonating at multiband of frequencies 3.5, 5.2, 6.3 and 8.4 GHz is developed. The variation in impedance of the antenna with respect to the antenna dimension is studied using artificial neural networks. A comparative study is made between the simulated bandwidth and MLPFFBP neural structure generated and RBF neural structure generated bandwidths. The proposed antenna gives a maximum bandwidth of 75 %, covering the frequency band 3.2 to 7 GHz. A 2×2 MIMO system is developed using the proposed antenna, and the mutual coupling between the antennas is studied with the help of ANNs for different values of separation between the antennas at various frequencies. This helps the MIMO antenna designer to develop a MIMO system at desired coupling levels conveniently, without going for simulation again and again.

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