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Research Article

A Generalized ANN Model for Analyzing and Synthesizing Rectangular, Circular, and Triangular Microstrip Antennas

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Since last one decade, artificial neural network (ANN) models have been used as fast computational technique for different performance parameters of microstrip antennas. Recently, the concept of creating a generalized neural approach for different performance parameters has been motivated in microstrip antennas. This paper illustrates a generalized neural approach for analyzing and synthesizing the rectangular, circular, and triangular MSAs, simultaneously. Such approach is very much required for the antenna designers for getting instant answer for the required parameters. Here, total seven performance parameters of three different MSAs are computed using generalized neural approach as such a method is rarely available in the open literature even for computing more than three performance parameters, simultaneously. The results thus obtained are in very good agreement with the measured results available in the referenced literature for all seven cases.

1. Introduction

Microstrip antennas are being widely used for different applications in wireless communication due to several attractive features: low profile, conformable to planar, and nonplanar surfaces, most economical, mechanically robust, light weight, easy mount-ability, and so forth. [1]. Since the microstrip antenna (MSA) operates only in the vicinity of resonance frequency, it needs to be calculated accurately for analyzing the microstrip antennas. Similarly, for designing the MSAs, the physical dimensions must also be calculated precisely. Several classical methods [2–14] have been used for computing the resonance frequency of rectangular MSAs [2–5], resonance frequency of circular MSAs [6–12], and resonance frequency of triangular MSAs [13, 14]. These methods can broadly be categorized as analytical methods and numerical methods. The analytical methods provide a good spontaneous explanation for the operation of MSAs. These methods are based on the physical assumptions for simplifying the radiation mechanism of the MSAs and are not suitable for many structures where the thickness of the substrate is not very thin. On the other hand, the numerical methods provide accurate results but only at the cost of huge mathematical burden in the form of complex integral equations. The choice of test function and path integration appears to be more critical without initial assumptions in the final stage of the numerical results. Also, these methods require a new solution even for a minor alteration in the geometry. Thus, the requirement for having a new solution for every minor change in the geometry as well as the problems associated with the thickness of the substrates in analytical methods leads to complexities and processing cost.

In recent years, the artificial neural network (ANN) models have acquired tremendous utilization in microwave communications [24–27] and, especially, in analyzing and synthesizing the MSAs [18–23, 28, 29] due to their ability and adaptability to learning, generalization, smaller information requirement, fast real-time operation, and ease of implementation features [24]. The ANN model is trained using measured, calculated, and/or simulated patterns. The aim of the training process is to minimize error between reference and actual outputs of the ANN model. Once the model is trained for a specified error, it returns the results very fast. For analyzing the MSAs, several neural models [18, 23, 28, 29] have been reported for calculating the resonance frequency of rectangular MSAs [18], the resonance frequency of circular MSAs [23], and the resonance frequency of triangular MSAs [28], respectively. For synthesizing the equilateral triangular

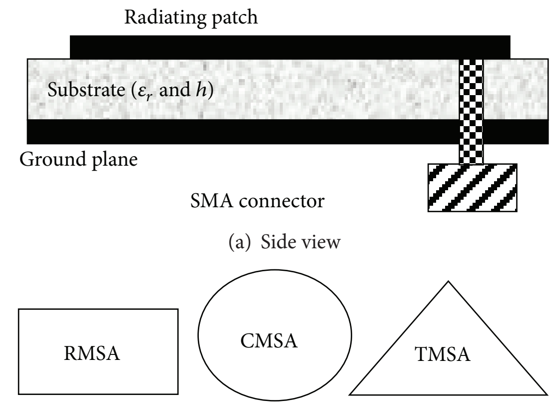
MSA, its side length has also been computed using neural network by Gopalakrishnan and Gunasekaran [29]. Thus, the neural methods [18, 23, 28, 29] have been used for computing a single parameter (i.e., the resonance frequency or physical dimension) of the same MSAs, respectively.

Recently, the concept for creating generalized neural models has gained popularity for computing different performance parameters, simultaneously [19–22]. Firstly, it has been introduced by Guney et al. [19] for computing the resonance frequencies of rectangular, circular, and triangular MSAs, simultaneously. Guney and Sarikaya [20, 21] have computed the resonance frequencies of rectangular, circular, and triangular MSAs, simultaneously, by introducing two different generalized methods; one is based on adaptive neural network-based fuzzy inference system (ANFIS) method [20] and another based on concurrent neurofuzzy system (CNFS) method [21]. Türker et al. [22] have proposed a generalized neural model for analyzing and synthesizing the rectangular MSAs, simultaneously. The synthesis of the problem has been defined as the forward-side and analysis as the reverse-side [21]. Thus, three different parameters, that is, resonance frequency, width, and length of rectangular MSAs, have been computed simultaneously in this model, whereas in ANFIS and CNFS methods, the three computed parameters have been mentioned as the resonance frequency of rectangular MSAs, resonance frequency of circular MSAs, and the resonance frequency of triangular MSAs. Further, the neural models [19–21] are based on the approach for calculating the equivalent area whereas the model [22] is based on making switching between forward- and reverse-side prior to calculating the desired parameter. For computing different parameters, simultaneously, in a common neural approach, sometimes it becomes undesirable and time consuming to the antenna designer when instant answer is required. In the proposed work, authors have proposed a simple and more accurate generalized neural approach for analyzing and synthesizing the rectangular, circular, and triangular MSAs, simultaneously as such an approach is rarely available in the referenced literature. The proposed approach is based in making equal dimensionality in the input patterns before applying training which has recently been applied in computing different performance parameters of triangular MSAs [30] and of circular MSAs [31].

2. Geometries for Patterns Generation

The microstrip antenna, in its simplest configuration, consists of a radiating conductive patch on one side of a dielectric substrate of relative permittivity, "ε_r" and of thickness, "h," having a ground plane on the other side [1]. The side-view of the proposed geometry with different radiating patches is shown in Figure 1. In Figure 1(b) RMSA corresponds to a rectangular MSA of physical dimensions, "W_r" and "L_r," CMSA to a circular MSA of radius, "R_c," and TMSA to an equilateral triangular MSA of side length, "S_t."

From the discussion made in conventional approaches [2–14], it is concluded that if the geometric dimensions, relative permittivity, dielectric thickness, and mode of propagation are given, then the resonance frequency can be calculated



(a) Side view

(b) Different radiating patches

Figure 1: Geometry of microstrip antenna.

easily. Keeping this concept in mind, total 81-patterns (46 for resonance frequency of rectangular MSAs, 20 for resonance frequency of circular MSAs, and 15-for resonance frequency of triangular MSAs) are arranged. 46-patterns for rectangular MSAs are obtained from the works of Chang et al. [2], Carver [3], and Kara [4, 5], 20-patterns for circular MSAs from the works of Dahele and Lee [6, 7], Carver [8], Antoszkiewicz and Shafai [9], Howell [10], Itoh and Mittra [11], and Abboud et al. [12], and 15-patterns for triangular MSAs are obtained from the works of Chen et al. [13] and Dahele and Lee [14]. These patterns are shown in Table 1.

As the microstrip antenna (MSA) has narrow bandwidth and operates only in the vicinity of the resonance frequency, the choice of geometric dimensions giving specific resonance is also important. The rectangular, circular, and triangular shapes of MSAs are the most popular shapes. Hence, for synthesizing the rectangular MSAs, the geometric dimensions ("W_r" and "L_r") can be computed from the given five input parameters; "f_r", "ε_r", "h", "m" and "n". For synthesizing the circular MSAs, its radius "R_c" can be estimated from the given five input parameters: "f_c," "ε_r," "h," "m," and "n." Similarly, for synthesizing the triangular MSAs, the side length can also be computed if the five input parameters: "f_t," "ε_r," "h," "m," and "n" are given. This concept is applied for creating the patterns required for synthesizing these three MSAs. Total 127 patterns (46 each for width and length of rectangular MSAs, 20 for radius of circular MSAs, and 15 for side length of triangular MSAs) are created and are shown in Table 2. Thus, 208 generated patterns (81 analysis patterns + 127 synthesis patterns), are used for training and testing of the ANN model to be discussed in Section 3.

3. Proposed ANN Modeling

In today's highly integrated world, when solutions to problems are cross-disciplinary in nature, ANNs promise to become powerful techniques for obtaining solutions to problems quickly and accurately. The ANNs are massively distributed parallel processors that have a natural propensity for storing experiential knowledge and making it available for

Table 1: Training and testing patterns [2–14] for analysis of MSAs.

(a)

Analysis of rectangular MSAs [2–5] Input parameters (6-dimensional)						
W_r (cm)	L_r (cm)	h (cm)	ε_r	m	n	f_r (GHz)
5.7000	3.8000	0.3175	2.3300	1	0	2.3100
4.5500	3.0500	0.3175	2.3300	1	0	2.8900
2.9500	1.9500	0.3175	2.3300	1	0	4.2400
1.9500	1.3000	0.3175	2.3300	1	0	5.8400
1.7000	1.1000	0.3175	2.3300	1	0	6.8000▲
1.4000	0.9000	0.3175	2.3300	1	0	7.7000
1.2000	0.8000	0.3175	2.3300	1	0	8.2700
1.0500	0.7000	0.3175	2.3300	1	0	9.1400
1.7000	1.1000	0.9525	2.3300	1	0	4.7300
1.7000	1.1000	0.1524	2.3300	1	0	7.8700
4.1000	4.1400	0.1524	2.5000	1	0	2.2280
6.8580	4.1400	0.1524	2.5000	1	0	2.2000▲
10.800	4.1400	0.1524	2.5000	1	0	2.1810
0.8500	1.2900	0.0170	2.2200	1	0	7.7400
0.7900	1.1850	0.0170	2.2200	1	0	8.4500▲
2.0000	2.5000	0.0790	2.2200	1	0	3.9700
1.0630	1.1830	0.0790	2.5500	1	0	7.7300
0.9100	1.0000	0.1270	10.200	1	0	4.6000
1.7200	1.8600	0.1570	2.3300	1	0	5.0600
1.8100	1.9600	0.1570	2.3300	1	0	4.8050▲
1.2700	1.3500	0.1630	2.5500	1	0	6.5600
1.5000	1.6210	0.1630	2.5500	1	0	5.6000
1.3370	1.4120	0.2000	2.5500	1	0	6.2000▲
1.1200	1.2000	0.2420	2.5500	1	0	7.0500
1.4030	1.4850	0.2520	2.5500	1	0	5.8000
1.5300	1.6300	0.3000	2.5000	1	0	5.2700
0.9050	1.0180	0.3000	2.5000	1	0	7.9900
1.1700	1.2800	0.3000	2.5000	1	0	6.5700
1.3750	1.5800	0.4760	2.5500	1	0	5.1000▲
0.7760	1.0800	0.3300	2.5500	1	0	8.0000
0.7900	1.2550	0.4000	2.5500	1	0	7.1340
0.9870	1.4500	0.4500	2.5500	1	0	6.0700
1.0000	1.5200	0.4760	2.5500	1	0	5.8200▲
0.8140	1.4400	0.4760	2.5500	1	0	6.3800
0.7900	1.6200	0.5500	2.5500	1	0	5.9900
1.2000	1.9700	0.6260	2.5500	1	0	4.6600
0.7830	2.3000	0.8540	2.5500	1	0	4.6000
1.2560	2.7560	0.9520	2.5500	1	0	3.5800▲
0.9740	2.6200	0.9520	2.5500	1	0	3.9800
1.0200	2.6400	0.9520	2.5500	1	0	3.9000
0.8830	2.6760	1.0000	2.5500	1	0	3.9800
0.7770	2.8350	1.1000	2.5500	1	0	3.9000
0.9200	3.1300	1.2000	2.5500	1	0	3.4700

(a) Continued.

Analysis of rectangular MSAs [2–5] Input parameters (6-dimensional)						
W_r (cm)	L_r (cm)	h (cm)	ε_r	m	n	f_r (GHz)
1.0300	3.3800	1.2810	2.5500	1	0	3.2000▲
1.2650	3.5000	1.2810	2.5500	1	0	2.9800
1.0800	3.4000	1.2810	2.5500	1	0	3.1500

(b)

Analysis of circular MSAs [6–12] Input parameters (5-dimensional)					
R_c (cm)	h (cm)	ε_r	m	n	f_c (GHz)
0.7400	0.1588	2.6500	1	1	6.6340
0.7700	0.2350	4.5500	1	1	4.9450
0.8200	0.1588	2.6500	1	1	6.0740
0.9600	0.1588	2.6500	1	1	5.2240▲
1.0400	0.2350	4.5500	1	1	3.7500
1.0700	0.1588	2.6500	1	1	4.7230
1.1500	0.1588	2.6500	1	1	4.4250
1.2700	0.0794	2.5900	1	1	4.0700
2.0000	0.2350	4.5500	1	1	2.0030
2.9900	0.2350	4.5500	1	1	1.3600▲
3.4930	0.1588	2.5000	1	1	1.5700
3.4930	0.3175	2.5000	1	1	1.5100
3.8000	0.1524	2.4900	1	1	1.4430
3.9750	0.2350	4.5500	1	1	1.0300
4.8500	0.3180	2.5200	1	1	1.0990
4.9500	0.2350	4.5500	1	1	0.8250
5.0000	0.1590	2.3200	1	1	1.1280
6.8000	0.0800	2.3200	1	1	0.8350
6.8000	0.1590	2.3200	1	1	0.8290▲
6.8000	0.3180	2.3200	1	1	0.8150

(c)

Analysis of triangular MSAs [13, 14] Input parameters (5-dimensional)					
S_t (cm)	h (cm)	ε_r	m	n	f_t (GHz)
4.1000	0.0700	10.5000	1	0	1.5190▲
4.1000	0.0700	10.5000	1	1	2.6370
4.1000	0.0700	10.5000	2	0	2.9950
4.1000	0.0700	10.5000	2	1	3.9730
4.1000	0.0700	10.5000	3	0	4.4390
8.7000	0.0780	2.3200	1	0	1.4890
8.7000	0.0780	2.3200	1	1	2.5960
8.7000	0.0780	2.3200	2	0	2.9690
8.7000	0.0780	2.3200	2	1	3.9680▲
8.7000	0.0780	2.3200	3	0	4.4430
10.0000	0.1590	2.3200	1	0	1.2800
10.0000	0.1590	2.3200	1	1	2.2420
10.0000	0.1590	2.3200	2	0	2.5500
10.0000	0.1590	2.3200	2	1	3.4000
10.0000	0.1590	2.3200	3	0	3.8240▲

▲Testing patterns.

Table 2: Training and testing patterns [2–14] for synthesis of MSAs.

(a)

Synthesis of rectangular MSAs [2–5]						
Input parameters (5-dimensional)					W_r (cm)	L_r (cm)
fr (GHz)	h (cm)	ε_r	m	n		
2.3100	0.3175	2.3300	1	0	5.7000	3.8000
2.8900	0.3175	2.3300	1	0	4.5500	3.0500
4.2400	0.3175	2.3300	1	0	2.9500	1.9500
5.8400	0.3175	2.3300	1	0	1.9500	1.3000
6.8000	0.3175	2.3300	1	0	1.7000▲	1.1000▲
7.7000	0.3175	2.3300	1	0	1.4000	0.9000
8.2700	0.3175	2.3300	1	0	1.2000	0.8000
9.1400	0.3175	2.3300	1	0	1.0500	0.7000
4.7300	0.9525	2.3300	1	0	1.7000	1.1000
7.8700	0.1524	2.3300	1	0	1.7000	1.1000
2.2280	0.1524	2.5000	1	0	4.1000	4.1400
2.2000	0.1524	2.5000	1	0	6.8580▲	4.1400▲
2.1810	0.1524	2.5000	1	0	10.800	4.1400
7.7400	0.0170	2.2200	1	0	0.8500	1.2900
8.4500	0.0170	2.2200	1	0	0.7900▲	1.1850▲
3.9700	0.0790	2.2200	1	0	2.0000	2.5000
7.7300	0.0790	2.5500	1	0	1.0630	1.1830
4.6000	0.1270	10.200	1	0	0.9100	1.0000
5.0600	0.1570	2.3300	1	0	1.7200	1.8600
4.8050	0.1570	2.3300	1	0	1.8100▲	1.9600▲
6.5600	0.1630	2.5500	1	0	1.2700	1.3500
5.6000	0.1630	2.5500	1	0	1.5000	1.6210
6.2000	0.2000	2.5500	1	0	1.3370▲	1.4120▲
7.0500	0.2420	2.5500	1	0	1.1200	1.2000
5.8000	0.2520	2.5500	1	0	1.4030	1.4850
5.2700	0.3000	2.5000	1	0	1.5300	1.6300
7.9900	0.3000	2.5000	1	0	0.9050	1.0180
6.5700	0.3000	2.5000	1	0	1.1700	1.2800
5.1000	0.4760	2.5500	1	0	1.3750▲	1.5800▲
8.0000	0.3300	2.5500	1	0	0.7760	1.0800
7.1340	0.4000	2.5500	1	0	0.7900	1.2550
6.0700	0.4500	2.5500	1	0	0.9870	1.4500
5.8200	0.4760	2.5500	1	0	1.0000▲	1.5200▲
6.3800	0.4760	2.5500	1	0	0.8140	1.4400
5.9900	0.5500	2.5500	1	0	0.7900	1.6200
4.6600	0.6260	2.5500	1	0	1.2000	1.9700
4.6000	0.8540	2.5500	1	0	0.7830	2.3000
3.5800	0.9520	2.5500	1	0	1.2560▲	2.7560▲
3.9800	0.9520	2.5500	1	0	0.9740	2.6200
3.9000	0.9520	2.5500	1	0	1.0200	2.6400
3.9800	1.0000	2.5500	1	0	0.8830	2.6760
3.9000	1.1000	2.5500	1	0	0.7770	2.8350
3.4700	1.2000	2.5500	1	0	0.9200	3.1300
3.2000	1.2810	2.5500	1	0	1.0300▲	3.3800▲
2.9800	1.2810	2.5500	1	0	1.2650	3.5000
3.1500	1.2810	2.5500	1	0	1.0800	3.4000

(b)

Synthesis of circular MSAs [6–12]					
Input parameters (5-dimensional)					R_c (cm)
f_c (GHz)	h (cm)	ε_r	m	n	
6.6340	0.1588	2.6500	1	1	0.7400
4.9450	0.2350	4.5500	1	1	0.7700
6.0740	0.1588	2.6500	1	1	0.8200
5.2240	0.1588	2.6500	1	1	0.9600▲
3.7500	0.2350	4.5500	1	1	1.0400
4.7230	0.1588	2.6500	1	1	1.0700
4.4250	0.1588	2.6500	1	1	1.1500
4.0700	0.0794	2.5900	1	1	1.2700
2.0030	0.2350	4.5500	1	1	2.0000
1.3600	0.2350	4.5500	1	1	2.9900▲
1.5700	0.1588	2.5000	1	1	3.4930
1.5100	0.3175	2.5000	1	1	3.4930
1.4430	0.1524	2.4900	1	1	3.8000
1.0300	0.2350	4.5500	1	1	3.9750
1.0990	0.3180	2.5200	1	1	4.8500
0.8250	0.2350	4.5500	1	1	4.9500
1.1280	0.1590	2.3200	1	1	5.0000
0.8350	0.0800	2.3200	1	1	6.8000
0.8290	0.1590	2.3200	1	1	6.8000▲
0.8150	0.3180	2.3200	1	1	6.8000

(c)

Synthesis of triangular MSAs [13, 14]					
Input parameters (5-dimensional)					S_t (cm)
f_t (GHz)	h (cm)	ε_r	m	n	
1.5190	0.0700	10.5000	1	0	4.1000▲
2.6370	0.0700	10.5000	1	1	4.1000
2.9950	0.0700	10.5000	2	0	4.1000
3.9730	0.0700	10.5000	2	1	4.1000
4.4390	0.0700	10.5000	3	0	4.1000
1.4890	0.0780	2.3200	1	0	8.7000
2.5960	0.0780	2.3200	1	1	8.7000
2.9690	0.0780	2.3200	2	0	8.7000
3.9680	0.0780	2.3200	2	1	8.7000▲
4.4430	0.0780	2.3200	3	0	8.7000
1.2800	0.1590	2.3200	1	0	10.0000
2.2420	0.1590	2.3200	1	1	10.0000
2.5500	0.1590	2.3200	2	0	10.0000
3.4000	0.1590	2.3200	2	1	10.0000
3.8240	0.1590	2.3200	3	0	10.0000▲

▲Testing patterns.

use. It resembles the brain since knowledge is acquired by the neural networks through learning process, and interneuron connection strengths are used to store this knowledge. Neural networks learn by known examples of a problem to acquire knowledge about it. Once the ANN trains successfully, it can be put to effective use in solving "unknown" or "untrained" instances of the problem [24]. Multilayered perceptron (MLP) and radial basis function (RBF) neural networks have primarily been used in computing different parameters of the MSAs [18–23, 28, 29]. A radial basis function (RBF) neural networks consists of three layers in which each layer is having entirely different roles. The input layer is made up of source nodes which connect the networks to the outside environment. The input layer does not accomplish any process but simply buffers the data. The hidden layer applies a Gaussian transformation from the input space to the hidden space [32]. The output layer is linear, supplying the response of the networks to the patterns applied at the input layer. As far as training of the neural networks is concerned, the RBF neural networks are much faster than the multilayers perceptron (MLP) neural networks. It is so because the learning process in RBF neural networks has two stages and both stages are made more efficient by using appropriate learning algorithms [32]. This is the prime reason of using RBF neural networks instead of MLP neural networks in present work. There are three common steps followed in applying RBF neural networks on the proposed problem. Firstly, the training patterns are generated, then the structural configuration of hidden layer neurons is selected in the second step, and, finally, in the third step the weights are optimized by using training algorithm. The trained neural model is then tested on the remaining arbitrary sets of samples not included in the training samples. These steps are being discussed here.

3.1. Patterns Generation and Their Dimensionality. The theoretical/experimental patterns mentioned in Tables 1 and 2 are used for training and testing the proposed neural model. It is clear from these tables that the dimensionality of input pattern is symmetrical in six different cases except for analyzing the rectangular MSAs. It means that the resonance frequency of the rectangular MSAs is the function of six dimensional input patterns, that is, $[W_r \quad L_r \quad \varepsilon_r \quad h \quad m \quad n]$, whereas the dimensionality of the input pattern is five in all six remaining cases. Hence, if the dimensionality of input pattern for the analysis of rectangular MSAs reduces from six to five, then it becomes compatible to the remaining six cases.

For the fundamental mode (i.e., $m = 1$ and $n = 0$) of rectangular MSAs, the resonance frequency depends on four parameters, that is, width and length of the patch and thickness and relative permittivity of the substrate. These four parameters dependency is represented by variables "x_1", "x_2", "x_3" and "x_4," respectively. The fundamental mode used here is not varying; hence, it can be represented by single integer "x_5" instead of integers "m" and "n" where $x_5 = 1$ means $m = 1$ and $n = 0$. Thus, the resonance frequency has become the function of five variables: "x_1," "x_2," "x_3," "x_4," and "x_5." The five-dimensional input patterns each for width and length calculation of the rectangular MSAs are mentioned as; the resonance frequency (x_1), dielectric thickness (x_2), relative permittivity (x_3), and modes of propagation (x_4 and x_5). The five-dimensional input patterns each for circular MSAs and triangular MSAs analysis as well as synthesis are also created using the same approach and represented by the variables x_1, x_2, x_3, x_4, and x_5, respectively. To distinguish these seven different cases an additional variable, "M", that is, a mode control, is also included in five-dimensional input patterns. The mode control, M, is selected as $M = 1$, $M = 2$, and $M = 3$ for computing the resonance frequency, width and length of rectangular MSAs, respectively, $M = 4$ and $M = 5$ for the resonance frequency and radius of circular MSAs, and, finally, $M = 6$ and $M = 7$ for calculating the resonance frequency and side length of the triangular MSAs, respectively. This six-dimensional input pattern, that is, $[x] \rightarrow [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad M]$, is used as the training and testing pattern for computing seven different parameters of three different MSAs, simultaneously. Thus, the input-output patterns with their original and modified dimensionalities for all seven different cases are also mentioned in Table 3.

3.2. Structural Configuration and Training Strategy. To build a successful neural-networks application, training stage is one of the most critical phases. Training the neural networks basically consists of adjusting weights of the neural networks with the help of a training algorithm. Before doing training of the RBF model, all 208 patterns are normalized between +0.1 and +0.9 using MATLAB software [33]. The training performance of the proposed neural networks is observed by varying the number of neurons in the hidden layer and after many trials it is optimized as forty-five neurons for the best performance. Further, the training performance of the neural model is also observed with seven different training algorithms [15–17]: BFGS quasi-Newton (BFG), Bayesian regulation (BR), scaled conjugate-gradient (SCG), Powell-Beale conjugate gradient (CGP), conjugate gradient with Fletcher-Peeves (CGF), one-step secant (OSS), and Levenberg-Marquardt (LM).

A RBF neural model proposed for computing seven different parameters is illustrated in Figure 2 in which the weight matrix is designated by *[w]* and the bias value by b, respectively. Initially, some random values are assigned for the weights which are then optimized using training algorithm and coding for this implementation is created in MATLAB software [33]. In Figure 2, the input matrix designated as $[x] \rightarrow [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad M]$ is of six-dimensional. The structural configuration of the proposed model is optimized as [6-45-1]. It means that there are 6 neurons in the input layer, 45 neurons in the hidden layer, and single neuron in the output layer. For the applied input pattern, some random numbers between *0* and *1* are assigned to the weights and the output of the model is computed corresponding to that input pattern. Some parameters like mean square error (MSE), learning rate, momentum coefficient, and spread value required during training of the neural model are taken as 5×10^{-7}, *0.1*, *0.5*, and *0.5*, respectively. The MSE between the calculated and referenced results is then computed for 169 training patterns and all the weights are updated accordingly. This updating process is carried out after presenting each set of input pattern until the calculated accuracy of the model is estimated satisfactory. Once it is achieved, the second phase, that is, testing algorithm, is created with the help of these updated weights for remaining 39 samples in the MATLAB software [33]. The arbitrary set out of total 39 testing sets is now applied on the model and its corresponding result is obtained, respectively.

Table 3: Dimensionality of input parameters for training and testing of ANN model.

Case-I ($M = 1$), resonance frequency of RMSAs		Case-II ($M = 2$), width of RMSAs	
Input parameters (x)	Output parameter (y)	Input parameters (x)	Output parameter (y)
$x_1 \rightarrow$ Width of the patch (W_r) $x_2 \rightarrow$ Length of the patch (L_r) $x_3 \rightarrow$ Dielectric thickness (h) $x_4 \rightarrow$ Relative permittivity (ε_r) $x_5 \rightarrow$ Mode of propagation (m and n)	Resonance frequency (MHz) of rectangular MSAs (Total 46 patterns)	$x_1 \rightarrow$ Resonance frequency (f_r) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)	Width (cm) of rectangular MSAs (Total 46 patterns)
Case-III ($M = 3$), length of RMSAs		**Case-IV ($M = 4$), resonance frequency of CMSAs**	
Input parameters (x)	Output parameter (y)	Input parameters (x)	Output parameter (y)
$x_1 \rightarrow$ Resonance frequency (f_r) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)	Length (cm) of rectangular MSAs (Total 46 patterns)	$x_1 \rightarrow$ Radius (R_c) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)	Resonance frequency (MHz) of Circular MSAs (Total 20 patterns)
Case-V ($M = 5$), radius of CMSAs		**Case-VI ($M = 6$), resonance frequency of TMSAs**	
Input parameters (x)	Output parameter (y)	Input parameters (x)	Output parameter (y)
$x_1 \rightarrow$ Resonance frequency (f_c) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)	Radius (cm) of circular MSAs (Total 20 patterns)	$x_1 \rightarrow$ Side-length of patch (S_t) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)	Resonance frequency (MHz) of triangular MSAs (Total 20 patterns)
Case-VII ($M = 7$), side length of TMSAs			
Input parameters (x)		Output parameter (y)	
$x_1 \rightarrow$ Resonance frequency (f_t) $x_2 \rightarrow$ Dielectric thickness (h) $x_3 \rightarrow$ Relative permittivity (ε_r) $x_4 \rightarrow$ Mode of propagation (m) $x_5 \rightarrow$ Mode of propagation (n)		Side-length (cm) of triangular MSAs (Total 20 patterns)	

Table 4: Comparison of average absolute error versus training algorithm.

Training algorithm [15–17]	Average absolute error in analysis and synthesis						Number of iteration required
	Rectangular MSAs		Circular MSAs		Triangular MSAs		
	Analysis	Synthesis	Analysis	Synthesis	Analysis	Synthesis	
BFG	11.35 MHz	1.1500 cm	34.10 MHz	1.8020 cm	13.20 MHz	1.4110 cm	13049
BR	31.33 MHz	2.1300 cm	27.20 MHz	1.0290 cm	22.70 MHz	1.1620 cm	12046
SCG	25.53 MHz	0.6800 cm	25.80 MHz	1.0310 cm	24.50 MHz	1.0110 cm	19602
CGB	5.100 MHz	1.0900 cm	15.10 MHz	1.2310 cm	35.40 MHz	0.0150 cm	14021
CGF	14.50 MHz	1.0300 cm	14.30 MHz	0.9160 cm	18.50 MHz	1.0130 cm	11302
OSS	21.80 MHz	1.7600 cm	1.020 MHz	2.1060 cm	23.70 MHz	1.2040 cm	14803
LM	3.200 MHz	0.0037 cm	0.700 MHz	0.0045 cm	1.600 MHz	0.0051 cm	1476

4. Calculated Results and Discussion

The training performance of the proposed generalized model is observed with seven different training algorithms: BFG, BR, SCG, CGP, CGF, OSS, and LM backpropagation algorithms, respectively, but only the Levenberg-Marquardt (LM) back propagation is proved to be the fastest converging training algorithm and produced the results with least mean square error (MSE) as mentioned in Table 4. To determine the most suitable implication given in the literature [2–14], the computed results are compared with the theoretical/experimental results reported in the literature. For analysis and synthesis of rectangular MSAs, this comparison is made with the experimental results of Chang et al. [2], Carver [3], and Kara [4, 5]. For circular MSAs analysis and synthesis, it is made with the experimental results of

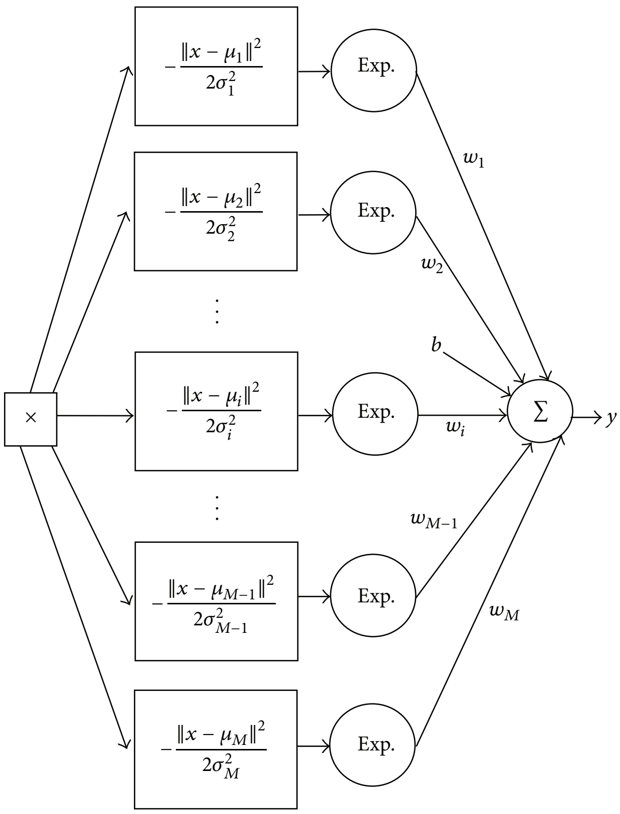


FIGURE 2: Proposed ANN model.

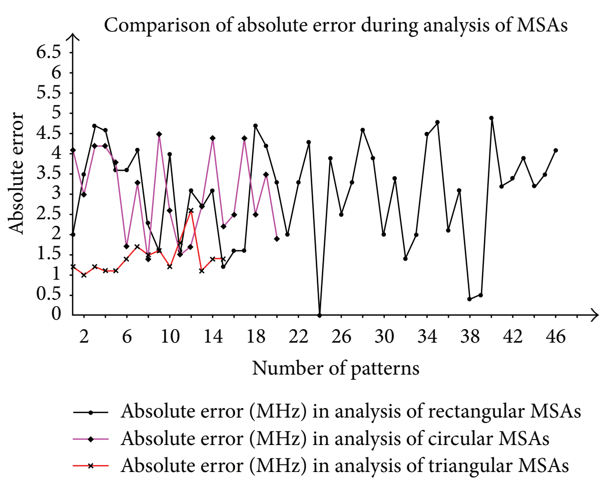


FIGURE 3: Absolute errors during analysis of rectangular, circular, and triangular MSAs.

Dahele and Lee [6, 7], Carver [8], Antoszkiewicz and Shafai [9], Howell [10], Itoh and Mittra [11], and Abboud et al. [12], whereas for equilateral triangular MSAs a comparison is made with the results of Chen et al. [13] and Dahele and Lee [14]. The absolute errors between the theoretical/experimental results and the computed results via ANN modeling are also calculated for analysis and synthesis of rectangular, circular, and triangular MSAs, respectively. This absolute error is plotted in Figure 3 for analysis of rectangular,

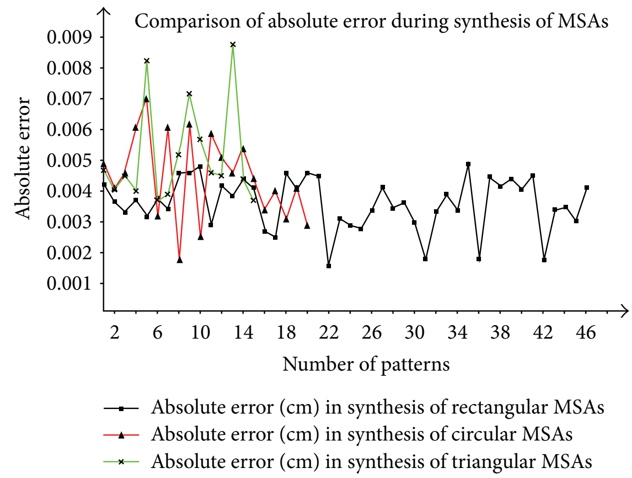


FIGURE 4: absolute errors during synthesis of rectangular, circular, and triangular MSAs.

circular, and triangular MSAs, respectively, and for synthesis of rectangular, circular, and triangular MSAs, it is plotted in Figure 4, respectively.

A comparison between the present method results and the results computed in previous neural models [18–23, 28, 29] is also given in Table 5. This table shows that in the neural models [18–22] the average absolute error for analyzing the rectangular MSAs has been calculated as 16.33 MHz, 71.88 MHz, 6.17 MHz, 16.88 MHz, and 50.0 MHz, whereas, in the present model it is only 3.2 MHz. In case of synthesizing the rectangular MSAs, the model [22] is having the average absolute error of 0.0041 cm whereas in present model it is calculated as 0.037 cm. In case of analyzing the circular MSAs, the proposed method is having the average absolute error of only 0.30 MHz, whereas in the methods [19–21, 23] it has been calculated as 0.55 MHz, 23.1 MHz, 4.55 MHz, and 0.35 MHz, respectively. For synthesizing the circular MSAs, the present model is having the average absolute error of 0.0045 cm whereas there is no neural model proposed for synthesizing the circular MSAs in the open literature [18–23, 28, 29]. For analyzing the equilateral triangular MSAs, the models [19–21, 28] are having average absolute errors as: 1.53 MHz, 18.33 MHz, 1.80 MHz, and 1.87 MHz, respectively, whereas, in the present model, it is calculated as 1.373 MHz and in case of synthesizing triangular MSAs, the average absolute error in testing patterns of the present method is only 0.0051 cm whereas in the model [29] it has been mentioned as 0.0090 cm. It is clear from the comparison given in Table 5 that the computed results by the proposed neural model are more accurate than the neural results of other scientists [18–23, 28, 29].

5. Conclusion

In this paper, authors have proposed a simple and accurate generalized neural approach for computing seven different parameters of three different microstrip antennas as there is no such neural approach suggested in the referenced literature even for computing more than three parameters,

Table 5: Comparison of the present method and previous neural methods.

Absolute error during analysis of rectangular MSAs					
Proposed method	[18]	[19]	[20]	[21]	[22]
3.20 MHz	16.33 MHz	71.88 MHz	6.17 MHz	16.88 MHz	50.0 MHz
Absolute error during synthesis of rectangular MSAs					
Proposed method	[22]	—	—	—	—
0.0037 cm	0.0041 cm	—	—	—	—
Absolute error during analysis of CMSAs					
Proposed method	[23]	[19]	[20]	[21]	—
0.30 MHz	0.55 MHz	23.1 MHz	4.55 MHz	0.35 MHz	—
Absolute error during synthesis of CMSAs					
Proposed method	[18–29]				
0.0045 cm	No neural model is available in the literature [18–29]				
Absolute error during analysis of TMSAs					
Proposed method	[28]	[19]	[20]	[21]	—
1.373 MHz	1.53 MHz	18.33 MHz	1.80 MHz	1.87 MHz	—
Absolute error during synthesis of TMSAs					
Proposed method	[29]	—	—	—	—
0.0051 cm	0.0090 cm	—	—	—	—

simultaneously. A neural model is rarely proposed in the literature for synthesizing the rectangular, circular, and triangular MSAs, simultaneously, or synthesizing the circular MSAs. The proposed generalized model has refined the requirement of these two synthesis models. As the proposed model has produced more encouraging results for all seven different cases, simultaneously without having any complicated structure and/or training strategy, it can be recommended to include in antenna CAD (computer-aided design) algorithms. The concept of the proposed approach is so simple and accurate that it can be generalized for large number of computing parameters depending upon the number of hidden nodes and the distribution of the input-output patterns. The approach can be very useful to antenna designers to accurately predict any desired parameter (i.e., resonance frequency of rectangular MSAs, width of rectangular MSAs, length of rectangular MSAs, resonance frequency of circular MSAs, radius of circular MSAs, resonance frequency of triangular MSAs, or side length of equilateral triangular MSAs) of the microstrip antennas by inputting its corresponding parameters within a friction of a second after doing training of proposed generalized neural method successfully.

In general, computing 7 different performance parameters may require 7 different neural networks modules, whereas in the present work, only one module is fulfilling the requirement of 7 independent modules. Hence, the present approach has been considered more generalized in this sense.

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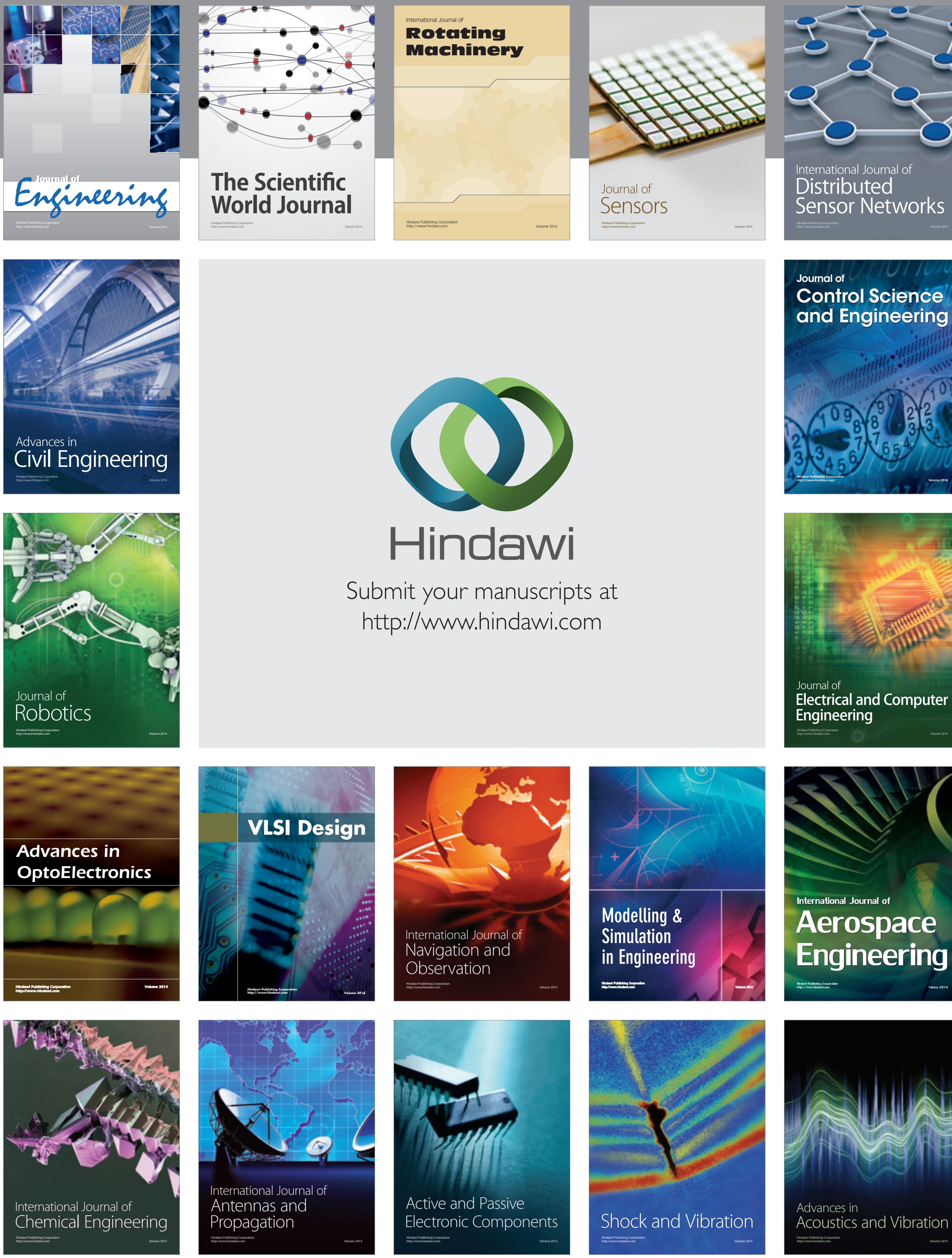
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