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Particle-Swarm-Optimization-Based Selective Neural Network Ensemble and Its Application to Modeling Resonant Frequency of Microstrip Antenna

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1. Introduction

From communication systems to biomedical systems, microstrip antennas (MSAs) are used in a broad range of applications, and this primarily due to their simplicity, conformability, low manufacturing cost, light weight, low profile, reproducibility, reliability, and ease in fabrication and integration with solid-state devices [1][2]. Recently, these attractive features have increased the applications of MSAs and stimulated greater effort to investigate their performance. In designing MSA, it is very important to determine its resonant frequencies accurately, because MSA has narrow bandwidths and can only operate effectively in the vicinity of the resonant frequency. So, a model to determine the resonant frequency is helpful in antenna designs. Several methods, varying in accuracy and computational effort, have been proposed and used to calculate the resonant frequency of rectangular MSA [3]-[13]. These methods can be broadly classified into two categories: analytical and numerical methods. Based on some fundamental simplifying physical assumptions regarding the radiation mechanism of antennas, the analytical methods are the most useful for practical design as well as providing a good intuitive explanation of the operation of MSAs. However, these methods are not suitable for many structures, in particular, if the thickness of the substrate is not very thin. The numerical methods provide accurate results but usually require tremendous computational effort and numerical procedures, resulting in roundoff errors, and may also need final experimental adjustment to the theoretical results. They suffer from a lack of computational efficiency, which in practice can restrict their usefulness due to high computational time and costs. The numerical methods also suffer from the fact that any change in the geometry, including patch shape, feeding method, addition of a cover layer, etc., requires the development of a new solution.

During the last decade, artificial neural network (NN) models have been increasingly used in the design of antennas, microwave devices, and circuits due to their ability and adaptability to learn, generalization, smaller information requirement, fast real-time operation, and ease of implementation features [14][15]. Through training process, a NN model can be developed by learning from measured/simulated data. The aim of the training process is to minimize error between target output and actual output of the NN. The trained NN model can be used during electromagnetic design to provide instant answers to the task it learned. Due to their attractive features, NN was used in computing the resonant frequencies of rectangular MSAs [16][17]. Reference [16] presented a NN model trained with the backpropagation (BP), delta-bar-delta (DBD), and extended delta-bar-delta (EDBD) algorithms for calculating the resonant frequencies of MSAs. The performance of this NN model was improved in reference [17] by using a parallel tabu search (PTS) algorithm for the training process. The results in [16] and [17] are not in very good agreement with the experimental results in literature [12] and [18] for the rectangular MSAs.

At present, neural network ensemble (NNE) has gradually become the hotspot in the field of machine learning and neural computation [19]. Through independently training several NNs and ensembling their computing results together, generalization ability of NNE modeling complex problems can be improved remarkably. In this chapter, selective NNE methods based on decimal particle swarm optimization (DePSO) algorithm and binary particle swarm optimization (BiPSO) algorithm are proposed. The NNs for constructing NNE are optimally selected in terms of particle swarm optimization (PSO) algorithm. This can maintain the diversity of NNs and decrease the effects of collinearity and noise of samples. At the same time, chaos mutation is adopted to increase the particles diversity of PSO algorithm. The next section briefly describes the computing method of resonant frequency of rectangular MSAs. The basic principles of PSO-based selective NNE are presented in the following section. Subsequently, the selective NNE is applied to the calculation of resonant frequency, and the computing results are better than available ones. The conclusions are then made.

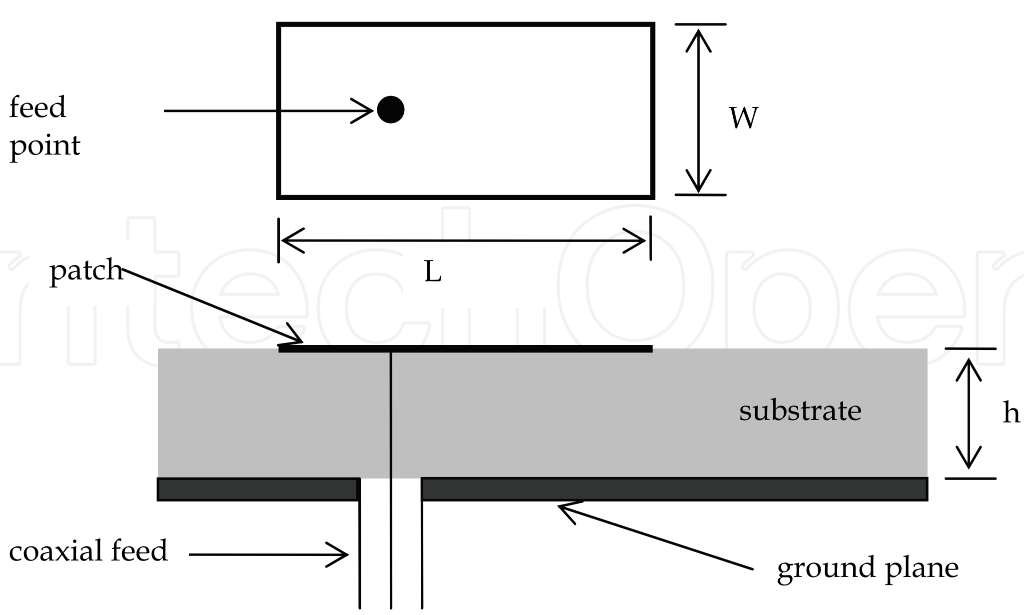

Fig. 1. Geometry of rectangular MSA

2. Resonant frequency of rectangular MSA

Fig. 1 illustrates a rectangular patch of width W and length L over a ground plane with a substrate of thickness h and a relative dielectric constant ε_r. The resonant frequency f_{mn} of the antenna can be calculated from (1) - (3) [1] [2].

$$f_{mn} = \frac{c}{2\sqrt{\varepsilon_e}}\left[\left(\frac{m}{L_e}\right)^2 + \left(\frac{n}{W_e}\right)^2\right]^{1/2} \tag{1}$$

Where ε_e is effective dielectric constant for the patch, c is velocity of electromagnetic waves in free space, m and n take integer values, and L_e and W_e are effective dimensions. To compute the resonant frequency of a rectangular patch antenna driven at its fundamental TM_{10} mode, expression (1) is written as

$$f_{10} = \frac{c}{2L_e\sqrt{\varepsilon_e}} \tag{2}$$

The effective length L_e can be defined as follows:

$$L_e = L + 2\Delta L \tag{3}$$

Where ΔL is edge extension, and its value is relative to the thickness h of the dielectric substrate.
Obviously, resonant frequency of the rectangular MSA is decided by h, ε_r, m, n and the size of patch W and L.

3. Particle swarm optimization algorithm

PSO, which was first developed by Kennedy and Eberhart[20], is a kind of evolutionary computational technology based on intelligent behavior of organisms, and its basic idea is originally from artificial life and evolutionary computation[21][22]. The main feature of PSO is to solve problems in real number field, the adjusted parameters are few, and it is a kind of general global research algorithm. Therefore, the method has been widely used in many fields, such as NN training, function optimization, fuzzy control system, etc.[23]. The advantages of PSO are characterized as simple, easy to implement, and efficient to compute. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. At present, as a robust global optimal method, PSO is also utilized in electromagnetic field [24][25], such as the design of absorbing material, antenna design and so forth.
PSO simulates the behaviors of bird flock [21][22]. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food being searched in the area. All the birds do not know where the food is. But they know how far the food is during each search iteration. So what's the best strategy to find the food? The effective one is to follow the bird that is nearest to the food. PSO learns from the scenario and uses it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values that are evaluated by the fitness function to be optimized, and have velocities that direct the flying of the particles. The

particles are "flown" through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called *pbest*. The other that is tracked by the particle swarm optimizer is the best value, which is obtained so far by any particle in the swarm. This best value is a global best and called *gbest*. After finding the two best values, the particle updates its velocity and position with following formulas:

$$v_{i,d}^{k+1} = \omega \cdot v_{i,d}^{k} + c_1 \cdot rand(\ ) \cdot \left(pbest_{i,d}^{k} - x_{i,d}^{k}\right) + c_2 \cdot rand(\ ) \cdot \left(gbest_{d}^{k} - x_{i,d}^{k}\right) \tag{4}$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1} \tag{5}$$

Where ω is inertia weight and control the PSO's exploitation ability and exploration ability. c_1 and c_2 are learning factors, and usually $c_1 = c_2 = 2$. $rand(\ )$ is a random number between (0,1). $v_{i,d}^{k}$ and $x_{i,d}^{k}$ are, respectively, velocity and position of particle i in dth dimension and kth iteration, and they are limited to a scope.

4. Neural Network and Neural Network ensemble

4.1 Neural Network

Neural Network (NN), which is also called Artificial Neural Network (ANN) in this study, is a simplified model to descript and abstract biological neural system of human brain according to mathematical and physical method and from the angle of information processing based on the understanding of human brain [26][27]. NN is a kind of description of characteristics of human brain system. Also, it is considered a computer system including many very simple processing units that connect each other in accordance with some manners. The system processes information on the basis of dynamic response of its state to external inputs. Simply speaking, NN is a mathematical model, and it can be implemented by electronic circuits or simulated by computer program. It is a kind of method in artificial intelligent (AI). Because NN can solve practical problems, its applying fields are expanded continuously, including not only engineering, science and mathematics but also iatrology, business, finance, and literature. To complex microwave engineering, it is very difficult to design by traditional manual methods, even not satisfy the demand. Therefore, rapid and efficient CAD (Computer aided design) method is urgently needed. From mathematical point of view, CAD model of electromagnetic problem is a kind of relationship of mapping, and NN can descript the relation effectively and accurately. Moreover, the computation of the mapping is convenient and fast. Because NN is very suitable for modeling and optimization of complex electromagnetic systems that face CAD optimized process, it is widely used in electromagnetic field [14][15].

4.2 Neural Network ensemble

NN has been successfully used in many fields. However, because of lack of instruction of rigorous theory, its applying effectiveness mainly depends on users' experience. Although feed fordward network with only one nonlinear hidden layer can approach functions with arbitrary complexity by arbitrary precision, the configuration and training of NN are NP

(Non-deterministic Polynomial) problem. In practical applications, model, algorithm and parameters of NN are determined only by many time-consuming experiments. Furthermore, the users of NN are ordinary engineers, and they are usually lack in applying experiences of NN. If there isn't easily used NN in engineering, the applying effectiveness of NN will be very difficult to be ensured. In 1990, Hansen and Salamon creationarily put forward the NNE (Neural network ensemble) method [19]. They proved that generalization ability of the neural computing system can be improved obviously by the way of training several NNs and then ensembling the results according to the rule of relative plurality voting or absolute plurality voting. Because the method is easy to use and its effectiveness is obvious, users without applying experiences of NN can get some benefits from it. Therefore, the NNE seems to be an effective neural computing method in engineering [28].

5. PSO-based selective NNE

5.1 Ensemble methods of NNs

An important research topic about NNE is its ensemble methods. This directly concerns its generalization ability. At present, the studies of ensemble methods mainly focus on two aspects: one is how to build/select every individual network; and the other is how to ensemble the outputs of every built/selected individual network. Taking the regression problem as an example, matrix inversion has to be carried out for getting combination weights of some conventional methods, and it is affected easily by multi-dimensional collinearity and noise in the data, which may decrease the generalization ability of the NNE [29][30]. In order to solve the problem of multi-dimensional collinearity, we can adopt some methods, such as, avoiding matrix inversion and restricting combination weights [29], selecting ensemble method [31], extracting principal components [29], and so on. In order to decrease the influence of noise, we can also adopt some methods, such as, restricting combination weights [32], adjusting objective function [32], and so forth. From the angles of avoiding matrix inversion and restricting combination weights, selective NNE methods based on DePSO and BiPSO are, respectively, adopted in this chapter. The basic idea of the methods is to optimally select NNs to construct NNE with the aid of PSO algorithm. This can maintain the diversity of individuals and decrease the effects of collinearity and noise of samples. Simultaneously, chaos mutation is injected into the iterative process to increase the particles diversity of PSO algorithm.

5.2 Implementation of PSO-based selective NNE

Assume that n NNs $f_1, f_2, \cdots, f_n$ have been trained separately, and apply them to construct NNE that approximate the mapping $f : \boldsymbol{R}^m \rightarrow \boldsymbol{R}^n$. In order to discuss the problem simply, assume every NN has only one output variable. Namely, the approximated mapping is $f : \boldsymbol{R}^m \rightarrow \boldsymbol{R}$. Obviously, the conclusion in this chapter may be extended easily to the situation with many output variables. The ensemble process can be achieved by using above-mentioned PSO algorithm. Every swarm of particles represent a kind of ensemble of $\{f_1, f_2, \cdots, f_n\}$, and particles length (dimension of particles space) equals to n that is the quantity of the NNs. We can adopt DePSO algorithm and BiPSO algorithm to achieve the network's selection.

To selective NNE based on DePSO algorithm, its actual output corresponding to the input $\boldsymbol{x}$ is given by

$$\bar{f}(\boldsymbol{x}) = \sum_{i=1}^{n} \bar{\beta}_i f_i(\boldsymbol{x}),\ \bar{\beta}_i = \frac{\beta_i}{\sum_{i=1}^{n} \beta_i} \tag{6}$$

where $\bar{\boldsymbol{\beta}}$ represents the importance (weight) of every NN in the ensemble, and it corresponds to the position vector in formula (5). Furthermore, it is optimized by above-mentioned DePSO algorithm.

To selective NNE based on BiPSO algorithm, the value of every particle in every dimension is discrete 0 or 1. If the value is 1, it indicates that the corresponding individual NN does participate the ensemble; if the value is 0, it indicates that the corresponding individual NN doesn't participate the ensemble. Therefore, the problem of selecting the individual NN to construct NNE can be transformed to the PSO problem that selects optimal particles in n-dimensional 0 and -1 space. The above-mentioned PSO algorithm can only be used in continuous space. In order to solve the optimal problems of discrete space, Kennedy proposed separate binary PSO algorithm [33]. To binary PSO algorithm, position of particle in every dimension has only two situations 0 or 1. The updating method of velocity is same as continuous PSO, but the updating method of position depends on the situation transition probability determined by the velocity of particle. The bigger the velocity is, the bigger the possibility of particle value being 1 becomes, and vise versa. The iterative formula is given by

$$x_{i,d}^{k+1} = \begin{cases} 1 & \rho_{i,d}^{k+1} \le sig\left(v_{i,d}^{k+1}\right) \\ 0 & \rho_{i,d}^{k+1} > sig\left(v_{i,d}^{k+1}\right) \end{cases} \tag{7}$$

where $\rho_{i,d}^{k+1} \in [0,1]$ is a random number. $sig(\cdot)$ is Sigmoid function, which is the velocity transform function. When adopting BiPSO algorithm constructs selective NNE, its actual output corresponding to the input $\boldsymbol{x}$ is given by

$$\bar{f}(\boldsymbol{x}) = \frac{\sum_{i=1}^{n} \beta_i f_i(\boldsymbol{x})}{Number} \tag{8}$$

Similarly, $\boldsymbol{\beta}$ represents to the position vector in formula (7), and *Number* represents the count of value 1 in $\boldsymbol{\beta}$.

In order to ensure the diversity of particles in the evolution process, velocity vector is mutated by chaos theory. Chaos is a significant concept in modern science, and it is also a very important content in nonlinear science [34]. Although it seems chaotic, its internal structure is exquisite. It is sensitive to initial conditions and has several advantages, such as randomicity, ergodicity, and regularity. Compared with general random search methods, its local search ability in a small area is excellent, and the effectiveness of detailed search is good. In this chapter, Logistic chaotic mapping is used to generate chaotic signals, and the iterative formula is as follows:

$$c^{k+1} = \mu c^k \left(1 - c^k\right) \tag{9}$$

where μ is control parameter. The Logistic chaos is complete when $\mu = 4$ and $0 < c^0 < 1$, $c^0 \ne 0.25$, $c^0 \ne 0.75$. After chaotic signal is generated, it is transformed to the optimized variables by the method of signal carrier, which makes them present chaotic state. Simultaneously, enlarge the ergodic scope of chaotic movement to the scope of optimized variables, and then directly search by using chaotic variables. After Chaotic signal is generated, $v_{i,d}^{k+1}$ in formula (7) is mutated by the following formula:

$$v_{i,d}^{k+1} = v_{i,d}^{k+1} + 2\alpha c^{k+1} - \alpha \tag{10}$$

where parameter α controls the extent of chaos mutation.

5.3 Numerical experiments

Experimental data is generated by Friedman # 1 function and Friedman # 3 function[29]-[31]. These two functions are representative and typical, and they are widely researched in regression analysis problem. The expressions of two functions are shown in table 1. Seven ensemble methods, which are simple evenness method (BEM) [29], generalized ensemble method (GEM) [20][21], linear regression (LR) method [29][30], principal components regression (PCR) method [29], genetic algorithm selective ensemble (GASEN) method [31], chaos DePSO method and chaos BiPSO method, are compared in this chapter.

According to every function's expression, 2200 data are generated, including 200 for training and the other 2000 for testing. By using NNs toolbox in Matlab, the variable gradient BP algorithm is used to train 20 networks. In order to ensure the differences of individual networks, the initial weights are generated randomly according to chaos theory. MSE_{train} and MSE_{test}, which respectively represent the mean square error of training set and testing set, show the generalization ability of NNE.

The computing results of Friedman # 1 function and Friedman # 3 function based on previously known methods are given in table 2, and computing results based on chaos DePSO method and chaos BiPSO method are given in table 3. In the computing process, the particles number is 30, the learning factors are selected according to the literature [35], namely $c_1 = 2.8$, $c_2 = 1.3$, the inertia weight ω in expression (4) changes linearly from 1 to 0.4 [36], and the evolutionary generation is 1000. In order to decrease the randomness, all of the ensemble methods are run 20 times repeatedly. The data in brackets of table 3 represent the count of NNs selected by the BiPSO algorithm when the corresponding computing result is gotten. Table 4 gives the statistic of NNs that participate the ensemble in all 20 times repeat computation in the BiPSO algorithm.

	Function expression	Variables range
Friedman # 1	$y = 10\sin(\pi x_1 x_2) + 20(x_3 - 0.5)^2 + 10x_4 + 5x_5$	$x_i \in U[0,1]$, $\varepsilon \sim N(0,1)$
Friedman # 3	$y = \tan^{-1}\left(\dfrac{x_2 x_3 - \dfrac{1}{x_2 x_4}}{x_1}\right) + \varepsilon$	$x_1 \in U[0,100]$, $x_2 \in U[40\pi, 560\pi$ $x_3 \in U[0,1]$, $x_4 \in U[0,11]$ $\varepsilon \sim N(0, 0.01)$

Table 1. Experimental functions

Ensemble methods	Friedman # 1		Friedman # 3 ($\times 10^{-2}$)	
	MSE_{train}	MSE_{test}	MSE_{train}	MSE_{test}
BEM	0.207	0.341	0.258	0.820
GEM	0.270	0.467	0.368	1.624
LR	0.270	0.469	0.370	1.638
PCR	0.184	0.280	0.288	0.960
GASEN	0.183	0.281	0.252	0.806

Table 2. Experimental results of known ensemble methods

Friedman # 1 function

Ensemble methods	MSE_{train} ($\times 10^{-2}$)			MSE_{test} ($\times 10^{-2}$)		
	Best	Worst	Average	Best	Worst	Average
BiPSO	0.5195(9)	1.1867(7)	0.7699	1.1189(8)	4.6976(13)	2.1402
DePSO	0.5516	1.0008	0.7334	1.3102	4.1716	2.3651

Friedman # 3 function

Ensemble methods	MSE_{train} ($\times 10^{-2}$)			MSE_{test} ($\times 10^{-2}$)		
	Best	Worst	Average	Best	Worst	Average
BiPSO	0.0815(11)	0.9503(7)	0.2584	0.1889(11)	1.3688(10)	0.8287
DePSO	0.0884	0.9799	0.2617	0.1895	1.5768	0.8346

Table 3. Experimental results based on ensemble methods in this study

	Friedman # 1							Friedman # 3							
Number of NNs	5	7	8	9	10	11	13	5	6	7	8	9	10	11	12
Statistic of appearance number	1	1	6	5	4	2	1	1	2	2	3	4	4	3	1

Table 4. Statistic of NNs that participate ensemble based on the BiPSO algorithm (The total repeat times is 20)

From the experimental results, we can safely draw the conclusions as follows.① Friedman # 1 function and Friedman # 3 function exist multi-dimension collinearity and noise problems. Due to low restraint to weights, existing matrix inverse and sensitiveness to noise, the ensemble performances by GEM and LR methods obviously are inferior to other methods. BEM highly restricts the weights, and it is insensitive to noise. PCR can eliminate some noise by extracting the principal components. GASEN adopts simple average method, and it can also suppress the noise. The BiPSO algorithm and the DePSO algorithm have high restraint to weights, and they can suppress the noise, too. Because all the last 5 methods can restrict weights, the performances of NNE decided by them are good. ② The influences of multi-dimension collinearity and noise to the BiPSO algorithm and DePSO algorithm are least, so the performances of NNE decided by these two algorithms are obviously better than these of GEM and LR methods as well as PCR. Compared with BEM and GASEN, to Friedman # 1 function, the BiPSO algorithm and the DePSO algorithm are obvious better than BEM and GASEN; to Friedman # 3 function, the BiPSO algorithm and the DePSO algorithm are almost same with BEM and GASEN. If we increase the iteration number of PSO, the computing results would get better. In addition, with the same evolutionary generation, the computing time of PSO algorithm is shorter than that of GASEN because of its simplicity.③ Table 3 shows that the computing results based on the BiPSO algorithm are a little better than that based on the DePSO algorithm. ④ Table 4 shows that, to the selective NNE based on the BiPSO algorithm, the statistic of NNs selected is around 8 to 10 generally.

6. Modeling resonant frequency of rectangular MSA by using BiPSO-Based selective NNE

Applying the above-discussed selective NNE based on the BiPSO algorithm models the resonant frequency of rectangular MSA at its fundamental TM_{10} mode. The input sample sets is (W,L,h, ε_r), and the output is corresponding measured resonant frequency f_{ME}. The trained NNE can give the mapping between the relative parameters of the rectangular MSA and its measured resonant frequency. The training and testing data sets used in this study have been obtained from previous experimental works [12] [18]. The relative data of the MSA are given from column 2 to column 5 of table 5, and the measured resonant frequency for TM mode are given in column 6 of table 5. Total 33 data sets are listed in table 5. Twenty-six data sets are used to train the NNE, and the remaining seven data sets, marked with an asterisk in table 5, are used for testing the NNE. Considering the influence caused by randomness, the program is run 20 times repeatedly, and the result is their average value. The computing results by using the method proposed in this chapter are given in column 7 of table 5, and the results obtained by using NN proposed by Guney [16] and by Sagiroglu and Kalinli [17] are given from column 8 to column 10 in table 5. The f_{EDBD}, f_{DBD}, f_{BP} and f_{PTS} in table 5 represent, respectively, the values calculated by using the NNs trained with EDBD(Extended delta-bar-delta), DBD(Delta-bar-delta), BP(Back propagation), and PTS(Parallel tabu search) algorithms. Simultaneously, the sum of absolute errors between theoretical and experimental results for every method is listed in table 5, too. Table 5 shows that the results computed by using the chaos BiPSO-based selective NNE are better agreement with the experimental results as compared with these of the previous NNs in [16] and [17], which means that the model of this chapter is better than previous ones. In order to make a further comparison, the resonant frequency of rectangular MSA obtained by

No	W (cm)	L (cm)	h (cm)	ε_r	Measured f_{ME}	$f_{BiPSO\text{-}NNE}$	f_{EDBD}[16]	f_{DBD}[16]	f_{BP}[16]	f_{PTS}[17]
1	0.850	1.290	0.017	2.22	7740	7764	7935.5	7890.1	7858.6	7847.4
2*	0.790	1.185	0.017	2.22	8450	8169	8328.2	8226.0	8233.1	8148.6
3	2.000	2.500	0.079	2.22	3970	3980	4046.4	4023.0	4075.4	3971.5
4	1.063	1.183	0.079	2.25	7730	7698	7590.1	7567.3	7616.8	7881.6
5	0.910	1.000	0.127	10.20	4600	4601	4604.8	4573.9	4592.4	4603.4
6	1.720	1.860	0.157	2.33	5060	5036	4934.2	4914.0	4930.3	4969.4
7*	1.810	1.960	0.157	2.33	4805	4796	4699.2	4684.8	4703.3	4879.0
8	1.270	1.350	0.163	2.55	6560	6559	6528.6	6502.8	6516.5	6635.8
9	1.500	1.621	0.163	2.55	5600	5605	5503.2	5473.3	5449.0	5516.3
10*	1.337	1.412	0.200	2.55	6200	6196	6176.6	6142.6	6147.2	6205.7
11	1.120	1.200	0.242	2.55	7050	7064	7099.6	7064.3	7132.9	7113.8
12	1.403	1.485	0.252	2.55	5800	5803	5805.6	5768.8	5765.7	5794.3
13	1.530	1.630	0.300	2.50	5270	5279	5287.7	5260.3	5254.0	5313.0
14	0.905	1.018	0.300	2.50	7990	7983	7975.5	7881.8	8002.2	7776.6
15	1.170	1.280	0.300	2.50	6570	6577	6674.8	6632.8	6682.7	6481.9
16*	1.375	1.580	0.476	2.55	5100	5182	5311.8	5293.2	5291.4	5191.4
17	0.776	1.080	0.330	2.55	8000	7948	7911.1	7841.6	7942.5	7893.0
18	0.790	1.255	0.400	2.55	7134	7176	7183.2	7162.1	7215.9	7267.0
19	0.987	1.450	0.450	2.55	6070	6092	6173.0	6155.1	6170.2	6030.4
20*	1.000	1.520	0.476	2.55	5820	5853	5931.0	5918.0	5924.5	5780.3
21	0.814	1.440	0.476	2.55	6380	6425	6424.0	6417.5	6430.7	6500.0
22	0.790	1.620	0.550	2.55	5990	5925	5866.1	5873.9	5870.5	6004.0
23	1.200	1.970	0.626	2.55	4660	4641	4699.0	4728.0	4718.9	4562.8
24	0.783	2.300	0.854	2.55	4600	4603	4459.1	4517.1	4519.2	4591.2
25*	1.256	2.756	0.952	2.55	3580	3614	3659.8	3655.7	3644.6	3685.2
26	0.974	2.620	0.952	2.55	3980	3977	3952.9	3982.6	3975.9	3948.5
27	1.020	2.640	0.952	2.55	3900	3912	3905.4	3930.0	3922.2	3891.4
28	0.883	2.676	1.000	2.55	3980	3986	3938.8	3970.7	3965.3	3969.4
29	0.777	2.835	1.100	2.55	3900	3895	3825.5	3851.1	3845.9	3893.0
30	0.920	3.130	1.200	2.55	3470	3472	3481.4	3466.2	3458.4	3456.9
31*	1.030	3.380	1.281	2.55	3200	3196	3230.3	3184.7	3178.0	3167.0
32	1.265	3.500	1.281	2.55	2980	2982	3036.1	2965.6	2961.2	3035.5
33	1.080	3.400	1.281	2.55	3150	3149	3191.2	3140.4	3134.0	3135.3
			Errors			863	2392	2427	2372	2239

*Test data sets. Resonant frequencies and errors are in MHz.

Table 5. Resonant frequency of rectangular MSAs for TM_{10} mode

No	f_{ME}	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10
1	7740	7804	7697	7750	7791	7635	7737	7763	772
2	8450	8496	8369	8431	8478	8298	8417	8446	839
3	3970	4027	3898	3949	3983	3838	3951	3950	391
4	7730	7940	7442	7605	7733	7322	7763	7639	755
5	4600	4697	4254	4407	4641	4455	4979	4759	461
6	5060	5283	4865	4989	5070	4741	5101	4958	492
7	4805	5014	4635	4749	4824	4520	4846	4724	468
8	6560	6958	6220	6421	6566	6067	6729	6382	635
9	5600	5795	5270	5424	5535	5158	5625	5414	537
10	6200	6653	5845	6053	6201	5682	6413	5987	598
11	7050	7828	6566	6867	7052	6320	7504	6682	676
12	5800	6325	5435	5653	5801	5259	6078	5552	558
13	5270	5820	4943	5155	5287	4762	5572	5030	508
14	7990	9319	7334	7813	7981	6917	8885	7339	757
15	6570	7412	6070	6390	6550	5794	7076	6135	626
16	5100	5945	4667	4993	5092	4407	5693	4678	483
17	8000	8698	6845	7546	7519	6464	8447	6889	716
18	7134	7485	5870	6601	6484	5525	7342	5904	617
19	6070	6478	5092	5660	5606	4803	6317	5125	534
20	5820	6180	4855	5423	5352	4576	6042	4886	510
21	6380	6523	5101	5823	5660	4784	6453	5122	539
22	5990	5798	4539	5264	5063	4239	5804	4550	483
23	4660	4768	3746	4227	4141	3526	4689	3770	394
24	4600	4084	3201	3824	3615	2938	4209	3168	344
25	3580	3408	2668	3115	2983	2485	3430	2670	284
26	3980	3585	2808	3335	3162	2590	3668	2790	301
27	3900	3558	2785	3299	3133	2573	3629	2771	298
28	3980	3510	2753	3294	3112	2522	3626	2721	296
29	3900	3313	2608	3147	2964	2364	3473	2554	282
30	3470	3001	2358	2838	2675	2146	3129	2317	254
31	3200	2779	2183	2623	2474	1992	2889	2151	235
32	2980	2684	2102	2502	2370	1936	2752	2086	225
33	3150	2763	2168	2600	2453	1982	2863	2139	233
Errors		13136	24097	11539	12322	30669	8468	22572	181

Resonant frequencies and errors are in MHz.

Table 6. Resonant frequency obtained from traditional methods for rectangular MSAs and sum of absolute errors between experimental results and theoretical results

conventional methods [3]-[13] are listed in table 6. The sum of absolute errors between experimental and theoretical results for every method is also listed in the last row of table 6. It is clear from table 5 and table 6 that the computing results of the chaos BiPSO-based selective NNE are better than these of previously proposed methods, which proves the validity of the algorithm further.

7. Conclusion

Selective neural network ensemble (NNE) methods based on decimal particle swarm optimization (DePSO) algorithm and binary particle swarm optimization (BiPSO) algorithm are proposed in this study. In these algorithms, optimally select neural networks (NNs) to construct NNE with the aid of particle swarm optimization (PSO) algorithm, which can maintain the diversity of NNs. In the process of ensemble, the performance of NNE may be improved by appropriate restriction on combination weights based on BiPSO algorithm. And this may avoid calculating the matrix inversion and decrease the multi-dimensional collinearity and the over-fitting problem of noise. In order to effectively ensure the particles diversity of PSO algorithm, chaos mutation is adopted during the iteration process according to randomicity, ergodicity and regularity in chaos theory. Experimental results show that the chaos BiPSO algorithm can improve the generalization ability of NNE. By using the chaos BiPSO-based selective NNE, resonant frequency of rectangular microstrip antenna (MSA) is modeled, and the computing results are better than available ones, which mean that the proposed NNE in this study is effective. The method of NNE proposed in this study may be conveniently extended to other microwave engineering and designs.

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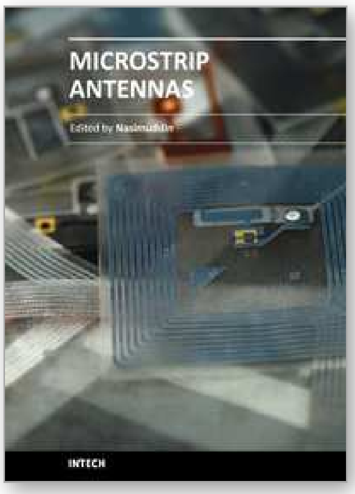

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In the last 40 years, the microstrip antenna has been developed for many communication systems such as radars, sensors, wireless, satellite, broadcasting, ultra-wideband, radio frequency identifications (RFIDs), reader devices etc. The progress in modern wireless communication systems has dramatically increased the demand for microstrip antennas. In this book some recent advances in microstrip antennas are presented.