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Particle Swarm Optimization-Based Rectangular Microstrip Antenna Designing

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***Abstract*— In this paper, a new system is proposed for microstrip antenna (MSA) designing. Two main stages need for designing procedure. Firstly, modeling of rectangular MSA is performed using some nonlinear regression methods. Then an inverse modeling is done using particle swarm optimization (PSO) algorithm with some constraints. Result includes a suitable system with bandwidth as an input and dimensions width, frequency range, length over a ground plane with a substrate thickness, dielectric loss tangent and electrical thickness as an output.**

***Index Terms*— Particle swarm optimization, Microstrip antennas, Nonlinear regression**

I. INTRODUCTION

Designing procedure can be performed based on modeling and inverse system. In this way, some experimental samples are captured from real system then it is modeled to form of a function $y = f(x_1, x_2, \ldots, x_n)$ where output of system is y and input features or parameters are $x_1, x_2, \ldots, x_n$. But in designing procedure we need suitable input parameters ($x_1, x_2, \ldots, x_n$) for receiving to desired(y), this step require an inverse modeling procedure. Main target in this paper is designing of rectangular microstrip antenna which after its modeling, bandwidth can be calculate using mathematical nonlinear model versus five input parameters include dimensions width, frequency range, length over a ground plane with a substrate thickness and dielectric loss tangent and electrical thickness. Then a artificial search algorithm is used for finding inverse model (Fig 1) that bandwidth is desire and dimensions width, frequency range, length over a ground plane with a substrate thickness and dielectric loss tangent and electrical thickness as outputs.

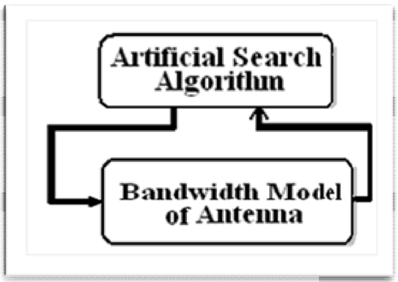

Fig. 1 Searching problem of optimum input parameters for obtaining desired bandwidth which is appeared in the future work

The used artificial search algorithm is swarm intelligent search. Kennedy and Eberhart [1, 2] introduced the Particle Swarm Optimization (PSO) method based on the simulation of bird flocking and fish schooling. PSO is a high performance optimizer that controls several highly desirable attributes, including the fact that the basic algorithm is very easy to comprehend and implement. It is similar in some ways to evolutionary algorithms, but needs less computation and generally fewer lines of code. This algorithm can optimize problem that requires the simultaneous optimization of N variables. It has attained its popularity due to a broad range of useful applications in such diverse areas as image compression [3], power system [4], phased array synthesis [5], RF circuit design [6], and digital filter design [7].

A. Scope of MSA

In recent years, the current trend in commercial and military communication systems has been to develop low cost, minimal weight, low profile planar configuration antennas ([8], [9] and [10]) that are capable of maintaining high performance over a large spectrum of frequencies. This technological trend has focused much effort into the design of microstrip (patch) antennas.

The concept of Microstrip antenna though introduced in the early 1950's in USA by Deschamps and in France by Gutton and Baissinot, it was in the 1970's only that with the advent of printed-circuit technology [11, 12], some serious advancements in this research area had begun resulting in the development of first practical antennas.

A Microstrip device in its simplest form is a sandwich of two parallel conducting layers separated by a single thin dielectric substrate. The upper conductor is a thin metallic patch (usually Copper or Gold), which is a small fraction of a wavelength [8]. The lower conductor is a ground plane which should be infinite theoretically. The patch and ground-plane are separated by a dielectric substrate which is usually non-magnetic. The patch can assume any shape, be it rectangular, circular, triangular, elliptical, helical, circular ring, etc. The variety in design that is possible with Microstrip antennas probably exceeds that of any other type of antenna element. Microstrip antennas are used where size, weight, cost, better performance, compatibility with microwave and millimeter wave integrated circuits (MMICs), robustness, ability to conform to planar and non-planar surfaces, etc. are required [11, 13].

Bandwidth and efficiency of a Microstrip antenna depends upon patch size, shape, substrate thickness, dielectric constant of substrate, feed point type and its location, etc. For good antenna performance, a thick dielectric substrate having a low dielectric constant is desirable for higher bandwidth, better efficiency and better radiation, leading to a larger

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antenna size. Designing a compact antenna requires higher dielectric constant, leading to narrower bandwidth, lesser efficiency and higher loss tangents (dissipation factors) [11].

In MSA designs, it is important to determine the bandwidth of the antenna accurately because the bandwidth is a critical parameter of a MSA. Several techniques [14, 15, 16], varying in accuracy and computational effort, have been proposed and used to calculate the bandwidth of a rectangular MSA, as this is one of the most popular and convenient shapes. The analytical techniques use simplifying physical assumptions, but generally offer simple and analytical solutions that are well-suited for an understanding of the physical phenomena and for antenna computer-aided design. These analytical techniques are known as transmission-line models and cavity models.

However, these techniques are not suitable for many structures, in particular, if the thickness of the substrate is not very thin. Most of the limitations of analytical techniques can be overcome by using the numerical techniques. The numerical techniques are based on an electromagnetic boundary problem, which leads to an expression as an integral equation, using proper Green functions, either in the spectral domain, (the SDA method), or directly in the space domain, using the method of moments. Without any initial assumption, the choice of test functions and the path integration appear to be more critical during the final, numerical solution.

Exact mathematical formulations in rigorous numerical methods involve extensive numerical procedures, resulting in round-off errors, and may also need final experimental adjustments to the theoretical results. These methods also suffer from the fact that any change in the geometry (patch shape, feeding method, addition of a cover layer, etc.) requires the development of a new solution. Furthermore, most of the previous theoretical and experimental work has been carried out only with electrically thin MSAs, normally of the order of $h/\lambda_d \leq 0.14$, where h is the thickness of the dielectric substrate and λ_d is the wavelength in the substrate.

Recent interest has developed in radiators etched on electrically thick substrates. This interest is primarily for two major reasons. First, as these antennas are used for applications with increasingly higher operating frequencies, and consequently shorter wavelength, even antennas with physically thin substrates become thick when compared to a certain wavelength. Second, the bandwidth of the rectangular MSA is typically very small for low profile, electrically thin configurations. One of the techniques to increase the bandwidth is to increase the thickness proportionately. The design of MSA elements having wider bandwidth is an area of major interest in MSA technology, particularly in the fields of electronic warfare, communication systems, and wideband radars. Consequently, this problem, particularly the bandwidth aspect, has received considerable attention.

The reminder of paper is organized as follows. In section 2, the bandwidth of an MSA is described, and then in section 3 MSA modeling is presented using nonlinear mathematical model. Section 4 includes the PSO-based designing procedure with a review on Particle Swarm Optimization (PSO) methods and its main parts for designing process. Experimentations are described in section 5 and finally section 6 draws conclusion of this paper.

II. Bandwidth of Rectangular Microstrip Antennas

The rectangular microstrip antennas are made of a rectangular patch with dimensions width, W and length, L, over a ground plane with a substrate thickness h and relative dielectric constants εr, as given in Fig.2.

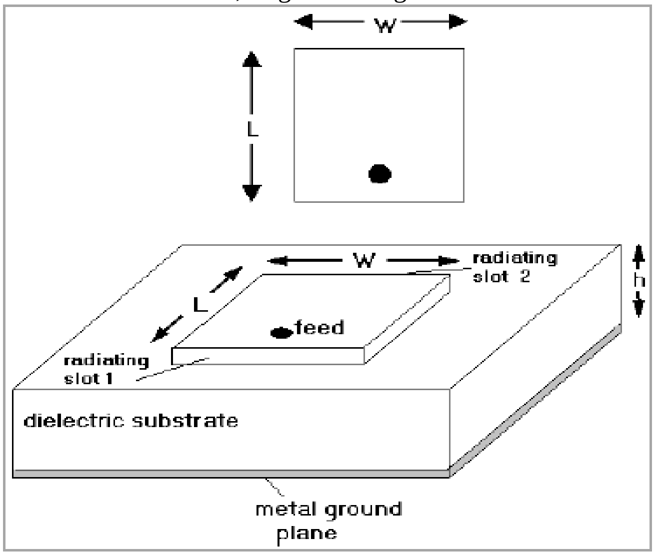


Fig.2. Rectangular microstrip antenna.

The bandwidth of this MSA can be determined from the frequency response of its equivalent circuit. For a parallel-type resonance, the bandwidth is expressed as [22]

$$BW = \frac{2G}{w_r \left.\frac{dB}{dw}\right|_{w_r}} \quad (1)$$

Where Y=G+jB is the input admittance at the angular resonant frequency w_r. For a series-type resonance, G is replaced by R and B is replaced by X in equation (1), where Z=R+jX is the input impedance at resonance. The bandwidth of a MSA can also be expressed as [21]

$$BW = \frac{s-1}{Q_T\sqrt{s}} \quad (2)$$

Where s is the voltage standing wave ratio (VSWR) and Q_T is the total quality factor. The total quality factor, Q_T, can be written as

$$\frac{1}{Q_T} = \frac{P_d + P_c + P_r + P_s}{w_r W_T} \quad (3)$$

Where P_d is the power lost in the lossy dielectric substrate, P_c is the power lost in the imperfect conductor, P_r is the power radiated in the space waves, P_s is the power radiated in the surface waves, and W_T is the total energy stored in the patch at resonance.

The wavelength in the dielectric substrate, l_d, is given as

$$l_d = \frac{l_0}{\sqrt{e_r}} = \frac{c}{f_r\sqrt{e_r}} \quad (4)$$

l_0 is the free space wavelength at the resonant frequency f_r and c is the velocity of electromagnetic waves in free space.

In this paper we introduce a novel method to calculate the bandwidth of rectangular MSAs based on Support Vector Regression (SVR). We use the parameters h, f_r, h/l_d, W and $\tan d$ for computation of Bandwidth.

III. Modeling of Bandwidth of Rectangular Microstrip Antennas

In this work, the SVR was used to compute the bandwidth of electrically thin and thick rectangular MSAs. For the SVR, the inputs are h, f_r, h/l_d, W and $\tan d$, and the output is the measured bandwidths *BWme*. The training and test data sets used in this paper have been obtained from previous experimental works [17, 18], and are given in Table 5 (which is appeared in Appendix). In this paper we used some kernel functions for SVR like polynomial with different degree, radial basis function and linear function. We use hold out and leave one out method for comparing average error of our proposed method with ANFIS (Adaptive Neuro Fuzzy Inference System) and results are shown in Table 1.

Table 1. Errors of SVR and ANFIS for bandwidths for electrically thin and thick rectangular microstrip antenna with leave one out and hold out method

Kernel	Average Error SVR		Average Error ANFIS	
	Leave one out	Hold out	Leave one out	Hold out
Poly, p=2	37.8586	0.0787	37.2162	0.1757
Poly, p=3	19.6580	0.1431	37.2162	0.1757
Poly, p=4	37.5095	0.1998	37.2162	0.1757
erbf	28.8429	0.0833	37.2162	0.1757
rbf	44.8668	0.2530	37.2162	0.1757
Linear	20.4241	0.0612	37.2162	0.1757

We can see in Table 1 that 'erbf' kernel function has less average error than ANFIS with both evaluation methods.

A. *Fine modeling*

As we mentioned before, the support vector machine is an approximate implementation of the method of structural risk minimization. This induction principle is based on the fact that the error rate of a learning machine on test data is bounded by the sum of the training-error and a term that depends on the Vapnik-Chervonenkis (VC) dimension. In this method, optimal hyper plane is determined to guarantee the minimum error for test samples, whereas, neural networks don't guarantee to find optimum hyper plane for test samples. So SVR give us better results relative to ANFIS as shown in section 4. But, some problems in the SVR are exists as follows:

a) Since each sample is one constraint in support vector, increasing training samples is equivalent to increasing number of constraints. In this case solving equations to find optimal hyper plane becomes very hard.

b) Finding suitable kernel for modeling of nonlinear space.

First Problem in the current work and similar works can be easily seen. For example for leave one out train and test procedure, we have 33 training samples and optimization problem must be solved with 33 constraints. The selection of suitable kernel given in the second problem is clear in Table 1 at a glance. So, we propose new version of SVR that works based on divide and conquer principle which can solves two aforementioned problems. Input space is divided to several subspaces and in each subspace a SVR models the data. This work is caused the new generated space has the properties of high dimensional space. A weighting procedure is performed using probability density function of each sub-space and gives portion of each SVR according to generated rules. Then results of weighted SVRs are combined and fitting is performed. We describe presented SVR method in detail in the following steps.

Step 1: In this step, we should divide input training data into n subsets. We can use an algorithm of clustering like fuzzy c-means (FCM) for this grouping. Indeed we assign the weights to any input data using FCM. Fig. 3 shows 3 partition (for example) which FCM has clustered. PDF (Probability Density Function) of each cluster are obtained as shown in the following figure then the corresponding weights of an input data are calculated based on membership values to each partitions (i.e. clusters).

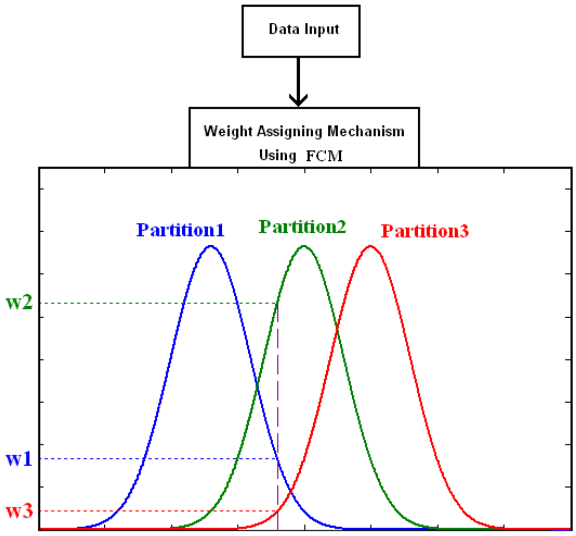


Fig. 3. Assigning weights to the input data

Step 2: Each available subset for any partition are applied for training of each Support Vector Regressor (SVR) like Fig. 4. So, for training samples of partition 1 (as shown in Fig.3) SVR1 is trained (as shown in Fig.4).

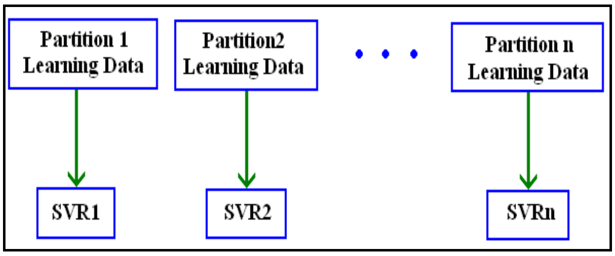


Fig. 4 Applying SVR in each partition

In this paper we used some kernel functions for SVR like polynomial with different degree, radial basis function and linear and check results for finding best state.

Step 3: Third step is testing procedure. We use leave one out method for computing average error of our proposed method and compare it with ANFIS. In order to calculate the output of the proposed system, we should compute membership values for each test sample (w_i). By applying equation (8) for any test sample, corresponding weights to the test samples are obtained and then we normalize these weights by dividing any weight to the sum of them. At the end, these normalized weights multiplied by each test sample for generating final values. Fig. 5 shows this procedure.

$$w_i = \frac{1}{2p\left|\tilde{\Sigma}\right|^{0.5}} \exp(-(x_t - m)\tilde{\Sigma}^{-1}(x_t - m)^T) \qquad (5)$$

Where $\tilde{\Sigma} = a\ \Sigma$ and Σ is covariance samples and μ is mean value of training data.

In equation (8), a is a variable to control of spreading of each Gaussian distribution that we consider for samples of training set. x_t is a test sample. Also $|\cdot|$ denotes to determinant.

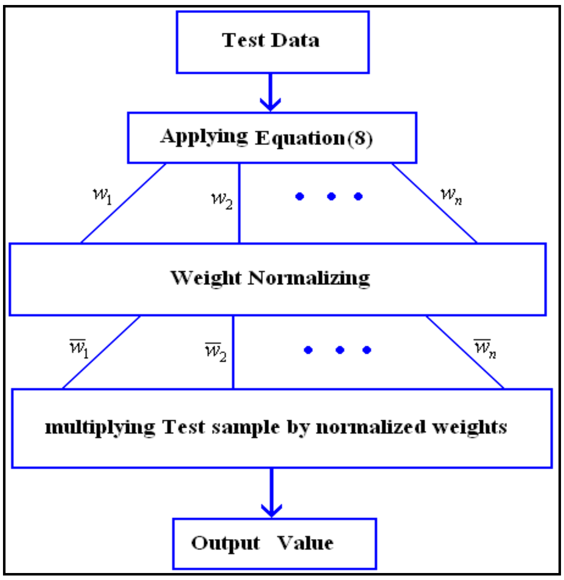


Fig. 5 Testing procedure

In Fig. 5 output value is computed value for bandwidth of MSA of test sample. In order to compute error of leave one out method for evaluation of performance of the proposed method, we can compute difference between computed value and measured value for bandwidth of MSA of any test sample and then obtained average value for all of data given in Table 5. We use leave one out method for performance testing of our proposed SVR against ANFIS with different kernel functions for SVR and different values for a (in this experiment we consider values 0.1, 0.2, …, 1 for a). Also the number of clusters is 2. For all values of α, average error of our method and ANFIS is shown in Table 2.

Table 2. Average error of our proposed SVR and ANFIS for calculation of bandwidths of MSA's

Kernel	Average error for all	Average Error ANFIS
erbf	0.01253	0.1984
rbf	0.32355	0.1984
Poly, p=2	0.07848	0.1984
Poly, p=3	0.07984	0.1984
Poly, p=4	0.07495	0.1984
Linear	0.05055	0.1984

Also we compare our proposed method with some conventional methods [21, 23, 24 and 25]. Fig. 6 shows comparison of computed error in calculating bandwidth of MSAs with mentioned conventional methods, ANFIS and our proposed SVR method. We use simple definition for computing error as absolute value of difference between measured BW [17 and 18] and computed value using each method.

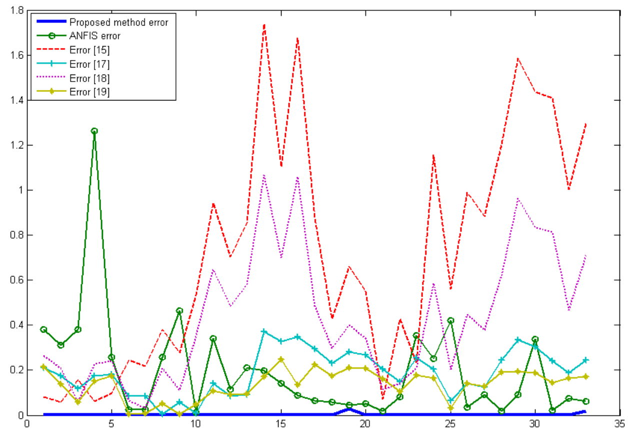


Fig. 6. Comparing error of some conventional methods and ANFIS with new SVR

Mean value of computed error for each method mentioned in Fig. 6 is as follows:

Table 3. Comparing conventional methods, ANFIS and proposed SVR for calculation of bandwidths of MSAs

Method	Error
[21]	0.7241
[23]	0.1891
[24]	0.4337
[25]	0.1359
ANFIS	0.1984
New SVR	0.002

IV. The PSO based Antenna Designing

In the previous section we try to model bandwidth of MSA which means that we want to predict corresponding bandwidth for given input parameters correctly. For this purpose SVR and a new version of SVR is used and the result of experimentations shows the ability of presented SVR against some approaches.

To perform a reverse action of modeling, we use particle swarm optimization (PSO) method to obtain a designing procedure.

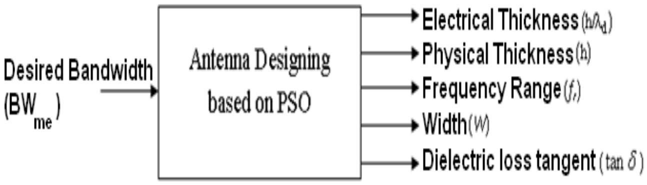


Fig. 7. Block diagram of antenna designing using PSO

As shown in Fig 1, an artificial search method can find best parameters for receiving of desired bandwidth. With search over input parameters in antenna model, desired bandwidth is obtained. Selected search method is PSO algorithm which is explained in the next sub-section. So after selection of desired bandwidth and constrains over required parameters as shown in Fig 7, PSO find these parameters based on founded model of antenna in the previous section.

In the next sub-sections, the PSO algorithm is described and then applying the search method is explained in antenna designing procedure.

A. Particle Swarm Optimization

Optimization is the process of making something better. Scientists invoke a new idea as particle swarm optimization (PSO) algorithm. The PSO was formulated by Kennedy at 1995 [1, 2]. The thought process behind the algorithm was motivated by the social behavior of animals, such as bird flocking or fish schooling. Each particle moves about the cost surface with a velocity. The particles update their velocities and positions based on the local and global best solutions. We consider $\vec{x}_i = (x_{i1}, x_{i2}, ..., x_{iN})$ and $\vec{v}_i = (v_{i1}, v_{i2}, ..., v_{iN})$ as the position and velocity of ith particle in N dimensional space. The motion of an object in PSO is represented as the vector sum of present position and velocity vectors as following equation:

$$\vec{x}_i^{k+1} = \vec{x}_i^k + \vec{v}_i^{k+1} \tag{6}$$

As k is an iteration index number. Also in the PSO equation, $\vec{p}_i = (p_{i1}, p_{i2}, ..., p_{iN})$ is the best position for ith particle in N dimensional space and $\vec{p}_g = (p_{g1}, p_{g2}, ..., p_{gN})$ would be best position for all particles. The second equation (7) comprises three vectors: inertia, competition, and cooperation. The cooperation vector $(c_2 rand \times (\vec{p}_g - \vec{x}_i^k))$ links the current position ($\vec{x}_i^k$) of a particle to the position of the best particle ($\vec{p}_g$); it is weighted using a uniformly distributed random function. Random function helps to find of global optima in the optimization problem. Each member of the group gains knowledge of the globally best position by cooperating and communicating with all other particles. The competition vector ($c_1 rand \times (\vec{p}_i - \vec{x}_i^k)$) links the current position of a particle to its personal best position $\vec{p}_i$, it is weighted using a second uniformly distributed random function. The competition factor describes the tendency of a particle to explore the vicinity of its own personal best position. Finally, the inertia vector ($w\vec{v}_i^k$) represents the partiality of a particle to maintain its current velocity; it is weighted by a constant. PSO cleverly joins inertia, competition, and cooperation in an optimum form so that the particles swarm to the best solution:

$$\vec{v}_i^{k+1} = w\vec{v}_i^k + c_1 rand \times (\vec{p}_i - \vec{x}_i^k) + c_2 rand \times (\vec{p}_g - \vec{x}_i^k) \tag{7}$$

The inertia weighting factor (w) is important in determining the balance between global and local search capabilities. If it is too large, PSO emphasizes global searching and is slow, and if it is too small, it emphasizes local searching and gets trapped in local minima. In this paper we use the following equation for finding adaptive weighting factor:

$$w = (w_{initialize} - w_{final}) \frac{(k_{\max} - k)}{k_{\max}} + w_{final} \tag{8}$$

Where $w_{initialize}$ initialize value of weight factor and final weight is w_{final} , and $k_{\max}$ is maximum iteration. In the first iteration k is equal zero and w is $w_{initialize}$ and gradually decreases to w_{final} . Nature of Randomness in the first iteration restricts us for following best member in the group until convergence occurs. Finally, tuning is necessary for decreasing mean square between optimal solution and founded variable.

B. Designing procedure

In this problem, we must search dimensions width (W), frequency range (f_r), length over a ground plane with a substrate thickness (h) and dielectric loss tangent ($\tan d$) and electrical thickness (h/λ_d) with some selected constrains with user for obtaining selected bandwidth. After finding parameters, they evaluate using founded model of antenna. If desired bandwidth is satisfied and optimum parameters stand in suitable range, designing procedure is terminated. We consider antenna designing to following form,

$$\text{Minimize } f(x_1, ..., x_m) \text{ Subject to} \\ a_i \le x_i \le b_i, \quad i = 1, ..., m \tag{9}$$

a_i, b_i are boundary of constants and $x \in R^n$.

Here $f(x_1, ..., x_m)$ is evaluation function and $a_i \le x_i \le b_i, \quad i = 1, ..., m$ are constrains. The PSO optimizer proposes a number of particles which each particle is one proposal for $x \in R^n$. These particles try to minimize $f(x_1, ..., x_m)$ subject to constraints. If one of particle in the colony cannot find suitable result, this means that particle (x with m dimension) cannot minimize $f(x_1, ..., x_m)$ or satisfy all constraints. So this particle should move in search space to solve problem. The particles will move in search space with $\vec{v}_i^k$ velocity which mentioned in the previous subsection. The following pseudo code describes our method.

Comment: *PSO-based antenna designing algorithm*
Comment: *Define the solution space, fitness function, and population size*
Initialize:
Minimum and maximum value of particles velocity in each dimension $[v_{\min}\ v_{\max}]$,
Maximum iteration, number of particles,
Minimum and maximum value of particles value in each dimension $[x_{\min}\ x_{\max}]$,
Initial and final value of Inertia weighting factor $\boldsymbol{w}$,
Determine initial value for particles $\boldsymbol{x}$.
While *Iteration <Max iteration*
Update inertia weighting factor $\boldsymbol{w}$
Call evaluation function; (**Comment:** Cost function)
Finding **pbest** and **gbest**;
Comment: pbest and **gbest** are best position for each and all particles respectively,
Update $\vec{v}_i^{k+1}$ and $\vec{x}_i^{k+1}$; (**Comment**: According to (7), (6))
End While
Display founded best $\vec{x}$.

This structure includes three main parts:

- **Cost function in the PSO algorithm for solving antenna designing problem.**
- **Velocity weights update control.**
- **Tuning procedure using adaptive velocity boundaries**

The PSO algorithm has been described in subsection 4.1 and here we explain matching it to this problem. $\vec{x}_i = (x_{i1}, x_{i2}, ..., x_{im})$ is ith particles with *m* dimensions. For this problem $f(x_1, ..., x_5)$ has five unknown variables, so *m* is five and $\vec{x}_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5})$ i.e. each particle propose one variable with *m* dimension. Cost function determine value of each particle and search is done based on cost of all particles as explained in subsection 4.1. Next sub-section includes the PSO cost function in antenna designing problems.

C. Cost function in the PSO algorithm

Now problem (9) transform to a suitable function which is solved using the PSO algorithm. In general, $f(x_1, ..., x_5)$ is nonlinear and applied to solve (9), then we can obtain an optimization problem:

$$f(x_1,...,x_5) = Desired\ \ Bandwidth - Bandwidth\ \ obtained\ \ from\ \ Antenna\ \ Model \quad (10)$$

Desired bandwidth is determined by user and it is the bandwidth that we want to find corresponding five parameters mentioned before for it. $f(x_1, ..., x_5)$ is calculated by subtracting desired bandwidth from bandwidth which is computed by model. As we described in detail in section 3, this model is based on SVR. Also some constraints must be applied over founded parameters which is described in the next section in details.

D. Velocity weights update control

In the standard PSO, the inertia weight is introduced as a decreasing function which is set to a higher value $w_{initialize} = 1$ and finally it receive to $w_{final} = 0.5$. Linear relation is defined per iteration according to following,

$$w = (w_{initialize} - w_{final})\frac{(k_{\max} - k)}{k_{\max}} + w_{final} \quad (11)$$

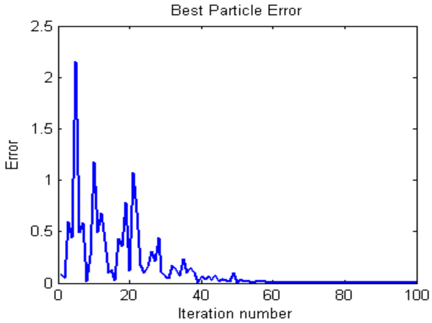
Where the initialize value of weight factor is $w_{initialize}$ and final weight is w_{final} , k is current iteration number and $k_{\max}$ is maximum iteration. In the first iteration k is equal zero and w is $w_{initialize}$ and gradually decreases to w_{final} . Nature of Randomness in the first iteration restricts us for following best member in the group until convergence occurs. Finally, tuning is necessary for decreasing mean square between optimal solution and founded variable.

E. Tuning procedure using adaptive velocity boundaries

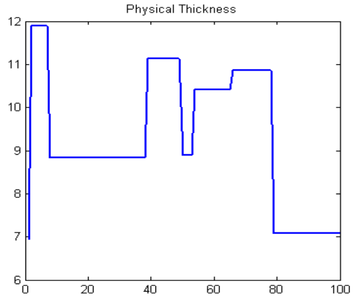
If velocity of each particle is bounded between $[v_{\min}, v_{\max}]$, controllability of PSO algorithm will be more. In the early iterations it is better we select particles with large boundary for minimum and maximum velocity. In this case particles try to fly to each area of search space. But gradually particles must move slowly which this work can performed with small velocity for $v_{\min}, v_{\max}$.

V. Experimental Result

Applied particles have five dimensions that they search space with various velocities. Velocity is started from high value and terminated to low value for fine searching. Physical thickness (h), frequency range (f_r), electrical thickness (h/l_d), dimension width (*W*) and dielectric loss tangent ($\tan d$) are variables. The antennas given in Table 5 vary in electrical thickness from 0.0065 to 0.2284, and in physical thickness from 0.17 to 12.81 mm, and operate over the frequency range 2.980–8.000 GHz. Their dimension width is in range 7.76-20.74 mm and dielectric loss tangent has values between 0.001 and 0.002. Also these constraints can change by user definition, which means that user can define more restricted boundaries for each variable to get arbitrary result. Suppose that maximum iteration is equal to 100. If desired bandwidth is 20, Fig. 8 and Fig.9 show error of the best particle in each iteration and obtained value for five variable.



(a)



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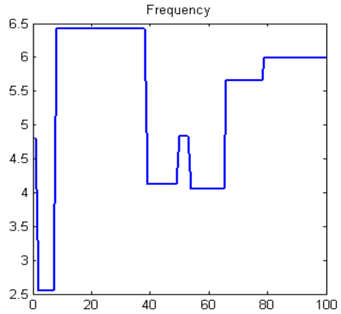
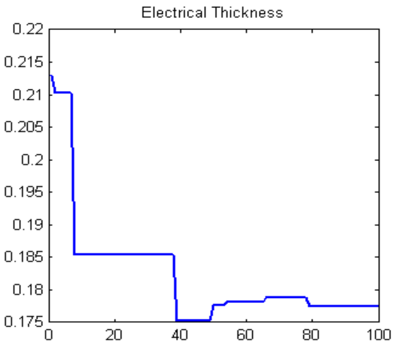
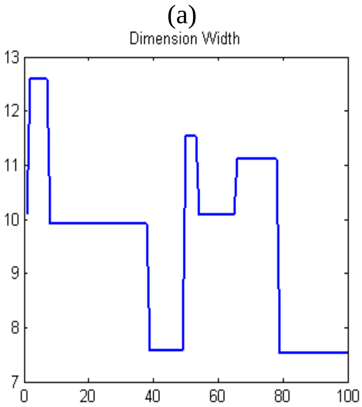


(c)

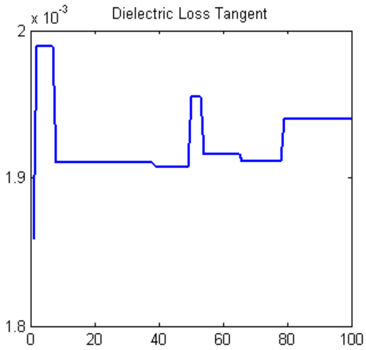
Fig. 8 (a) Absolute value of error that the best particle found, (b) Obtained value for Physical Thickness and (c) Obtained value for Frequency



(a)



(b)



(c)

Fig. 9 (a) Obtained value for Electrical Thickness, (b) Obtained value for Dimension Width and (c) Obtained value for Dielectric Loss Tangent

In order to evaluate performance of our method, computed values of parameters by PSO in each iteration are applied in SVR for calculating corresponding bandwidth and then these bandwidth are compared to desired bandwidth (desired bandwidth is equal to 20 in this case). Fig. 10 shows the result of this comparison.

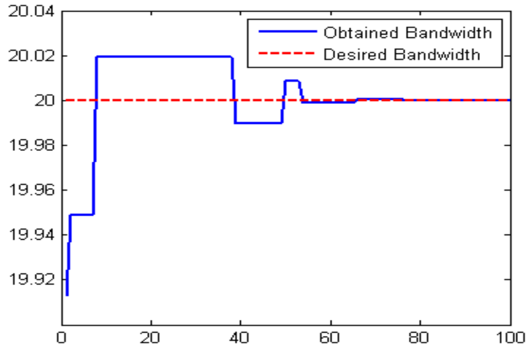
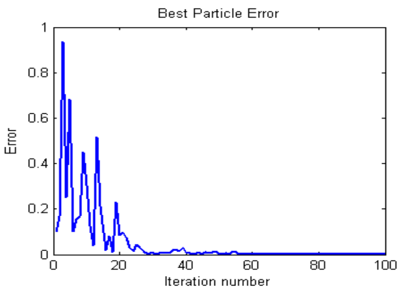


Fig. 10 Obtained bandwidth and desired bandwidth comparison

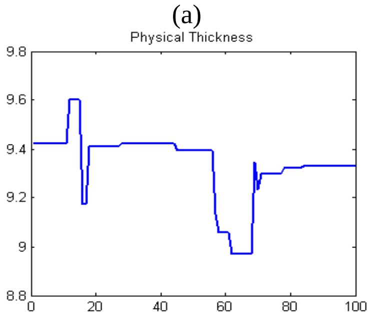
A. Constraints effect

It is mentioned before that user can select boundary of each variable more restricted. This change in constraints affects the results. For example for bandwidth 20 which we peruse it before, if we restrict constraints of variables more (correct sub-region), we get less error than the obtained error with previous constraints (a guided search). Of course for some sub-regions, it may not find any solution; for example for physical thickness, if we select limitation range between 1 to 4, and other parameters are selected as like the previous example, divergence is occurred. So we conclude some sub-range may give divergence. Fig. 11 and Fig. 12 show error of the best particle and obtained values for each variable for following ranges.

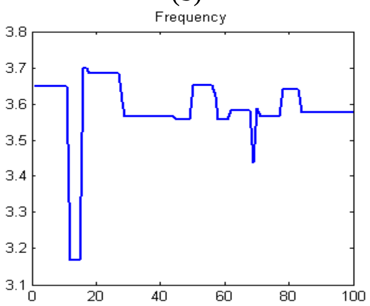
Physical thickness has values in 8.5-9.8mm; frequency range is 3-4 GHz; dimension width is in range 12 to 13mm and electrical thickness and dielectric loss tangent are selected like before.



(a)

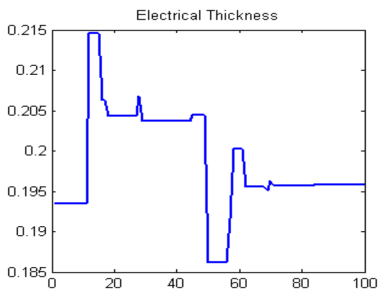


(b)

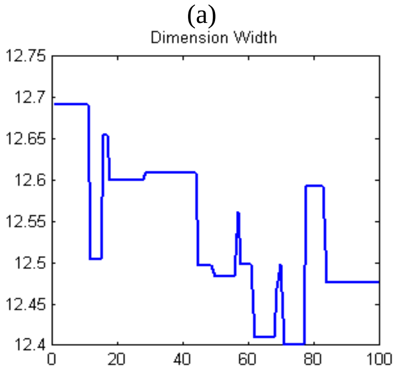


(c)

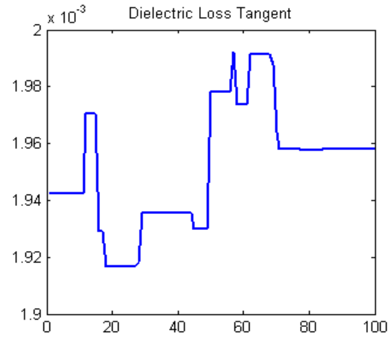
Fig. 11 (a) Absolute value of error that the best particle found, (b) Obtained value for Physical Thickness and (c) Obtained value for Frequency



(a)



(b)



(c)

Fig. 12 (a) Obtained value for Electrical Thickness, (b) Obtained value for Dimension Width and (c) Obtained value for Dielectric Loss Tangent

As like Fig. 10, we can compare desired bandwidth with obtained bandwidths using SVR method with input parameters that PSO found. Fig. 13 shows this comparison. Also from this figure we find that, since we use guided search by more limited boundaries for five antenna parameters, we reach the desired bandwidth sooner.

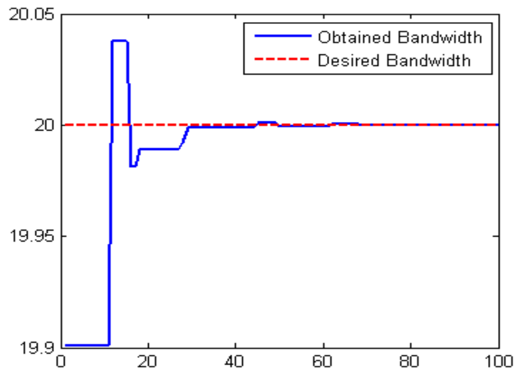


Fig. 13 Obtained bandwidth and desired bandwidth comparison

It is necessary to note that for convergence of results, range of velocity of each particle should be in -0.05 to 0.1, otherwise PSO search process is diverged. Corresponding constraints used for MSA designing are summarized in Table 4.

Table 4. MSA parameters and their limitation ranges

MSA parameters	Range
Physical Thickness (h)	[0.17,12.81]
Frequency (f_r)	[2.98,8]
Electrical thickness (h/λ_d)	[0.0065,0.2248]
Dimension width (W)	[7.76,20.74]
Dielectric Loss Tangent (tan δ)	[0.001,0.002]

VI. Conclusion

A PSO based approach for designing microstrip antennas was presented in this paper. Also in order to find a model for bandwidth calculation of MSA we used a nonlinear mathematical method namely SVR. A new version of SVR was proposed to reduce bandwidth prediction error than SVR. Thereafter designing procedure based on PSO for antenna designing problem was proposed in detail. The results of experimentations showed the ability of our method to find suitable parameters for antenna designing.

APPENDIX

The training and test data sets used in this paper have been obtained from previous experimental works [17, 18], and are given in Table 5. The 27 data sets in Table 5 were used to train the SVR. The 6 data sets, marked with an asterisk in Table 5, were used for testing. The training and test data sets used in this paper are also the same as those used for ANNs [19, 15] and FISs [20]. The antennas given in Table 5 vary in electrical thickness from 0.0065 to 0.2284, and in physical thickness from 0.17 to 12.81 mm, and operate over the frequency range 2.980–8.000 GHz.

Table 5. The measured bandwidths for electrically thin and thick rectangular microstrip antennas

Patch no	h (mm)	F_r(GHZ)	h/l_d	W (mm)	$\tan d$	Measured [17, 18] BW_{me} (%)
1	0.17	7.740	0.0065	8.50	0.001	1.070
2	0.79	3.970	0.0155	20.00	0.001	2.200
3	0.79	7.730	0.0326	10.63	0.001	3.850
4	0.79	3.545	0.0149	20.74	0.002	1.950
5	1.27	4.600	0.0622	9.10	0.001	2.050
6	1.57	5.060	0.0404	17.20	0.001	5.100
7*	1.57	4.805	0.0384	18.10	0.001	4.900
8	1.63	6.560	0.0569	12.70	0.002	6.800
9	1.63	5.600	0.0486	15.00	0.002	5.700
10*	2.00	6.200	0.0660	13.37	0.002	7.700
11	2.42	7.050	0.0908	11.20	0.002	10.900
12	2.52	5.800	0.0778	14.03	0.002	9.300
13	3.00	5.270	0.0833	15.30	0.002	10.000
14*	3.00	7.990	0.1263	9.05	0.002	16.000
15	3.00	6.570	0.1039	11.70	0.002	13.600
16	4.76	5.100	0.1292	13.75	0.002	15.900
17	3.30	8.000	0.1405	7.76	0.002	17.500
18*	4.00	7.134	0.1519	7.90	0.002	18.200
19	4.50	6.070	0.1454	9.87	0.002	17.900
20	4.76	5.820	0.1475	10.00	0.002	18.000
21	4.76	6.380	0.1617	8.14	0.002	19.000
22	5.50	5.990	0.1754	7.90	0.002	20.000
23	6.26	4.660	0.1553	12.00	0.002	18.700
24	8.54	4.600	0.2091	7.83	0.002	20.900
25	9.52	3.580	0.1814	12.56	0.002	20.000
26	9.52	3.980	0.2017	9.74	0.002	20.600
27*	9.52	3.900	0.1976	10.20	0.002	20.300
28	10.00	3.980	0.2119	8.83	0.002	20.900
29	11.00	3.900	0.2284	7.77	0.002	21.960
30	12.00	3.470	0.2216	9.20	0.002	21.500
31	12.81	3.200	0.2182	10.30	0.002	21.600
32	12.81	2.980	0.2032	12.65	0.002	20.400
33*	12.81	3.150	0.2148	10.80	0.002	21.200

*Test data set

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