Genetic Based Approach to the Synthesis of a Cylindrical-Rectangular Microstrip Conformal Antenna Using Artificial Neural Network and Support Vector Regression Models

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Abstract

In this paper, a rectangular microstrip antenna which is conformed to a cylindrical surface is synthesized by using Genetic Algorithm (GA), Support Vector Regression (SVR) and Artificial Neural Networks (ANN). GA is used to obtain the desired resonant frequency via trained SVR and ANN models. The results obtained by SVR and ANN models are compared.

1. Introduction

Conformal antennas are desirable where aerodynamic and hydrodynamic effects are substantial. So they are widely used in many fields of application like satellites, missiles, aircrafts, etc. The most important advantage of conformal antennas is that they take the shape of the curved surface so they do not interfere with aerodynamic and hydrodynamic performance of the structure [1]. However, there is no analytical formula to calculate the performance parameters of the conformal antenna. Also, due to the curved shape, numerical analysis and electromagnetic simulations involve high computational cost and require much time. To obtain the performance parameters, designers mainly use trial and error method. This increases the time-spent and successful results are not guaranteed.

In order to overcome these difficulties, Artificial Neural Networks (ANN) have drawn attention in last years due to their adaptability, generalization and non-linearity properties. ANNs have been used in many studies to obtain performance parameters of antennas and microwave devices [2-10]. Despite these advantages, ANNs have some drawbacks. There is no effective way to determine the number of hidden layers and neurons. Also assuring that ANNs generalize correctly is a difficult task [11].

Support Vector Machines (SVM), proposed by Vapnik [12], have proved to be superior than ANNs due to their better generalization capabilities. SVMs are used to solve both classification and regression problems. SVMs which are used in regression problems are called Support Vector Regression Machines (SVR). In technical literature, there are works where SVRs have been used in microwave systems and antennas [11,13,14].

As far as the authors know, there is no analytical expression for the computation of the resonant frequency of a rectangular microstrip cylindrical conformal antenna in the literature. So, in this work, SVR and ANN are used to obtain a model instead of an analytical function. In order to obtain the desired resonant frequency of a rectangular microstrip antenna which is conformed to a cylindrical surface, Genetic Algorithm (GA) is employed to obtain resonant frequencies from SVR and ANN.

Genetic Algorithm, inspired by the concepts of evolution and natural selection [15,16], has been successfully applied in electromagnetics. In GA, each member of population is called a chromosome. Natural selection, cross-over and mutation operations alter the chromosomes and better offspring chromosomes are obtained.

In this study, the resonant frequency of a conformal antenna which has random geometric variables (length and width), has been obtained by both SVR and ANN. Then, GA has been used to acquire the length and the width of the antenna for the desired resonant frequency computed from SVR and ANN models. The results obtained by SVR and ANN have been compared.

2. Support Vector Regression

Suppose a given training data D has P total number of elements; $D = \{(x^1, y^1), \dots, (x^n, y^n)\}$. Approximation of this data set by a linear function is given by [11,17];

$$f(x) = \langle w, g(x) \rangle + b \qquad (1)$$

where *w* is a weighting vector, *b* is bias and *g(x)* is a non-linear mapping vector. To solve this problem, the risk function [11,17];

$$\Phi(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_i (\xi_i^- + \xi_i^+) \qquad (2)$$

is minimized where ξ_i^+ and ξ_i^- are slack variables of upper and lower constraints of system and *C* is a user defined regularization parameter. In most of the cases, *D* will not be linearly separable [17]. Therefore, generally a nonlinear mapping is carried out through the kernel function ;$K(x_i, x_j)$ to a high dimensional space where linear regression can be performed. Most frequently used kernel functions are polynomial, linear and radial basis kernel (RBF) functions [14].

To predict the results of the new input samples, closed form of *f(x)* has to be obtained. This is possible if the SVR is trained with a suitable data set. A loss function is iteratively optimized. Vapnik's ε-insensitive loss function [11,17] is given by:

$$L_{\varepsilon}(\mathrm{y})=\begin{cases} 0 & |f(x)-y|<\varepsilon \\ |f(x)-y| & else \end{cases} \quad (3)$$

3. Synthesis Procedure for the Cylindrical-Rectangular Microstrip Conformal Antenna

GA based approach uses SVR or ANN in order to obtain the desired resonant frequency for the conformal antenna. Inputs of the SVR and ANN are the length (L) and width (W) of the conformal antenna. SVR or ANN is separately used to find the resonant frequency of the antenna for given L and W. GA is used to obtain L and W for the desired resonant frequency. Firstly, SVR and ANN are trained with a suitable training pattern computed by High Frequency Structural Simulator (HFSS) and an initial population for the GA is created. Number of chromosomes in the population is Q and chromosomes have L and W values as variables (genes). Then trained SVR and ANN compute the resonant frequency for each chromosome containing L and W. Cost value of each chromosome is calculated by the following cost function;

$$cost = |f_d - f_c| \quad (4)$$

where f_d is the desired resonant frequency and f_c is the computed resonant frequency. Chromosomes are sorted by their cost values and half of the population is eliminated by natural selection. After natural selection, cross-over and mutation processes are carried out. If the desired resonant frequency is obtained with minimum error by at least one of the chromosomes, algorithm is terminated.

Flow chart of the synthesis procedure is given in Fig. 1.

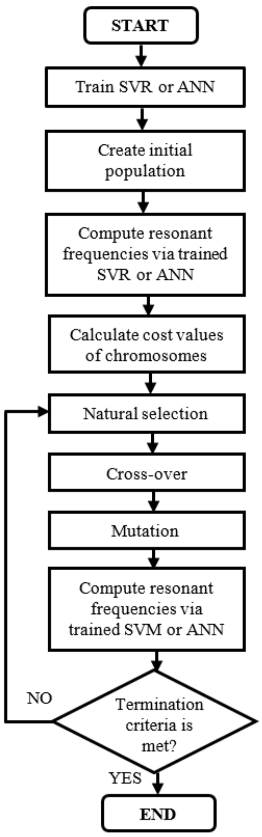

Fig. 1. Flow chart of the synthesis procedure

4. Training and Testing with SVR and ANN

A rectangular antenna which is conformed to a cylindrical surface has been used in this study. FR-4 substrate has dielectric permittivity $\varepsilon_r = 4.7$ and thickness $h = 2mm$. High Frequency Structural Simulator (HFSS) [18] drawing of microstrip line fed cylindrical conformal antenna is shown in Fig. 2. L and H values of the conformal antenna have been optimized via GA.

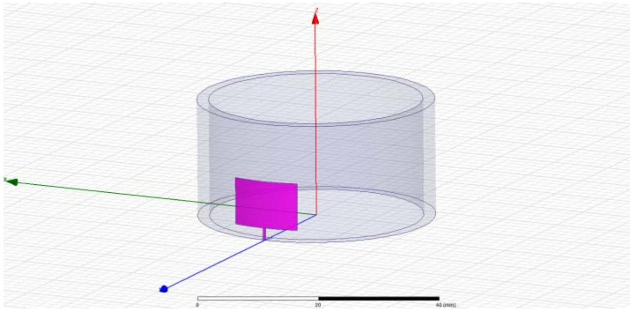

Fig. 2. HFSS drawing of the cylindrical conformal antenna

Firstly, in order to show the superiority of SVR over ANN, training and testing results are compared. Training pattern is constructed by using HFSS. Sampling strategy for training and testing patterns is given in Table 1. For the one element in pattern set, HFSS simulation time is 2 min 13 sec and for the whole pattern HFSS simulation time is 1 h 23 min with a computer with 4.0 GHz CPU and 16GB RAM.

Table 1. Sampling strategy

Length(L)	$9mm \leq L \leq 16mm$
Width(W)	$9mm \leq W \leq 16mm$
Total number of samples	256
Training samples	200
Test samples	56

ANN and SVR models are given in Fig. 3. Input [I] includes [L W] and output [O] includes resonant frequency [f].

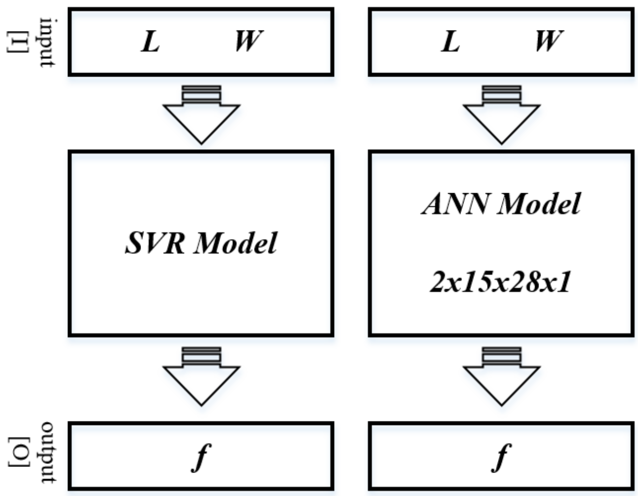

Fig 3. SVR and ANN models

SVR parameters and ANN parameters are given in Table 2. and Table 3. A Radial basis function (RBF) Kernel has been used with: .

$$K(x,x') = \exp(-(x-x')^2/2\sigma^2) \tag{5}$$

Table 2. SVR parameters

Kernel function	Radial Basis Function (RBF)
Regularization parameter(C)	10^{12}
$\boldsymbol{\varepsilon}$	10^{-4}
γ	10^{3}
σ	15

Table 3. ANN parameters

Configuration	$2 \times 15 \times 28 \times 1$
Network Type	*FFBPN*
Training Algorithm	LM
Number of Epoch	1000

Firstly, ANN has been trained with the patterns given in Table 1. A multilayer perceptron (MLP) ANN with a configuration of $2 \times 15 \times 28 \times 1$ has been used. The network type has been chosen as feedforward backpropagation network (FFBPN) and Levenberg-Marquardt (LM) algorithm has been used in training.

The training time of FFBPN has been recorded as 6.312 sec. Result of testing via trained ANN with 56 test samples is given in Fig. 4. Mean accuracy with ANN has been calculated as 95.83%. Sample frequencies are obtained via HFSS simulation and test frequencies are obtained via SVR and ANN.

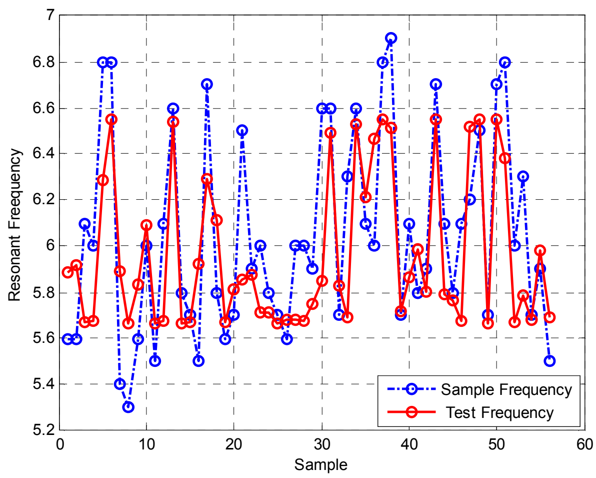

Fig. 4. Test results for ANN trained data

SVR has been trained by using RBF kernel. Training time is 2.924 sec. Mean accuracy with SVR has been calculated as 99.49%. Test results with SVR are given in Fig. 5. It can be observed that SVR accuracy is better than ANN. SVR can find better results with less time consumption. Sample frequencies are obtained via HFSS simulation and test frequencies are obtained via SVR.

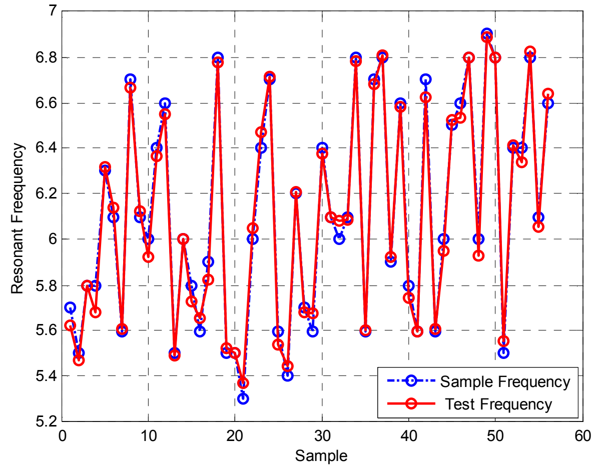

Fig. 5. Test results for SVR trained data

5. Optimization Results

GA has been used to obtain *L* and *W* for the desired resonant frequency of the conformal antenna from SVR and ANN models. Conformal antenna structure is given in Fig 2. The same samples of section 3 have been employed. 200 training samples have been used to train SVR and ANN. Optimization parameters are given in Table 4.

Table 4. Optimization parameters

Number of chromosomes(Q)	50
Number of generations(M)	50
Number of variables(P)	0.4
Probability of cross-over(p_c)	0.1
Probability of cross-over(p_m)	2
Optimization range for L and W	[9mm,16mm]

Firstly, SVR has been trained with samples given in Table 1. Then trained SVR has been used in the optimization algorithm as the generator of resonant frequency. Desired resonant frequency f_d is selected as 5.5 GHz. Cost function values with respect to iteration number for 5.5 GHz are given in Fig. 6.

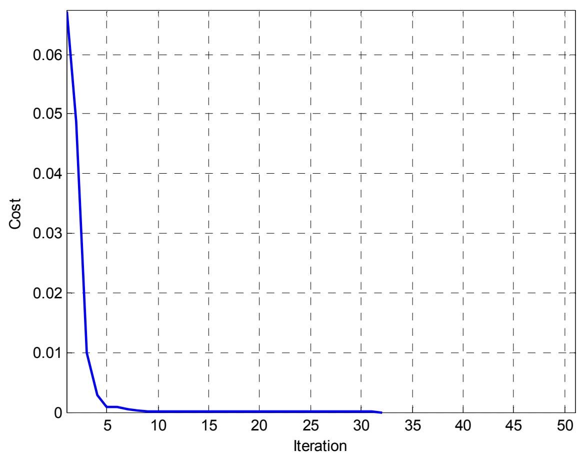

Fig. 6. Convergence of GA for SVR (dF_r=5.5GHz)

GA converges at the 32th iteration. Elapsed time during optimization is 3.66 sec. Obtained L and W values via optimization for f_d=5.5 GHz are L=11.8751 mm and W=11.9619mm. In order to check the resonant frequency with L and W values which are found via optimization, HFSS simulation has been carried out. $|S_{11}|$ graph of HFSS simulation is given in Fig. 7. Resonant frequency is obtained as 5.6 GHz in HFSS. Error between resonant frequencies of simulation and optimization is 1.81%.

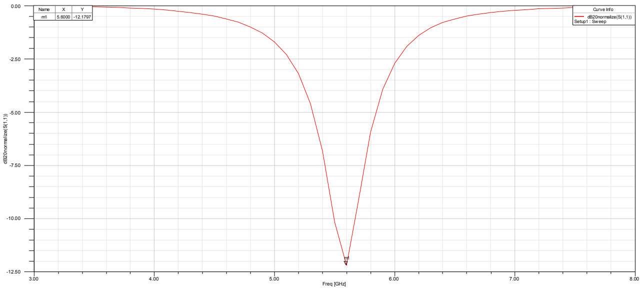

Fig. 7. $|S_{11}|$ value for f_d=5.5 GHz with L=11.8751mm and W=11.9619

As another example, desired resonant frequency f_d is selected as 6.5 GHz. Cost function values with respect to iteration number for 6.5 GHz are given in Fig. 8.

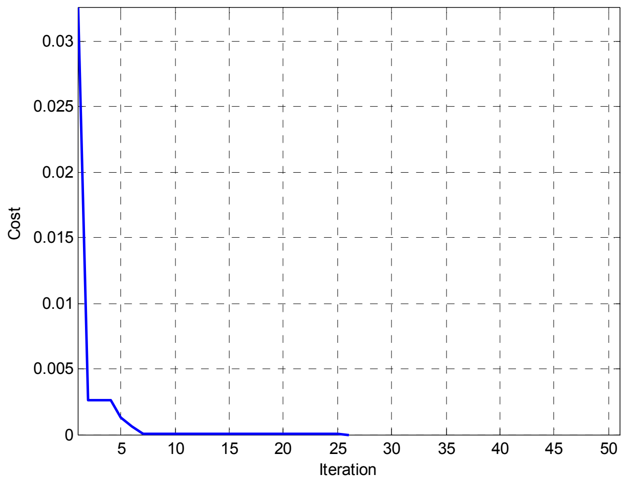

Fig. 8. Convergence of GA for SVR (f_d =6.5GHz)

GA converges at the 26th iteration. Elapsed time during optimization is 3.37 sec. Obtained L and W values via optimization for f_d =6.5GHz are L=9.7010mm and W=12.1673mm. $|S_{11}|$ graph of HFSS simulation is given in Fig. 9. Resonant frequency is obtained as 6.6 GHz in HFSS. Error between resonant frequencies of simulation and optimization is 1.53%.

ANN has also been used for training. Trained ANN is employed as resonant frequency generator in GA based optimizer. Cost function values with respect to iteration number for 6 GHz are given in Fig. 10.

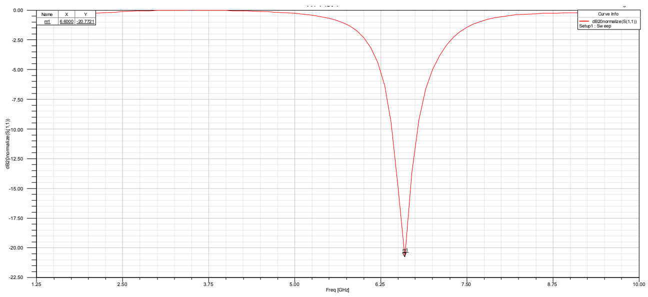

Fig. 9. $|S_{11}|$ value for f_d =6.5GHz with L=9.7010 mm and W=12.1673 mm

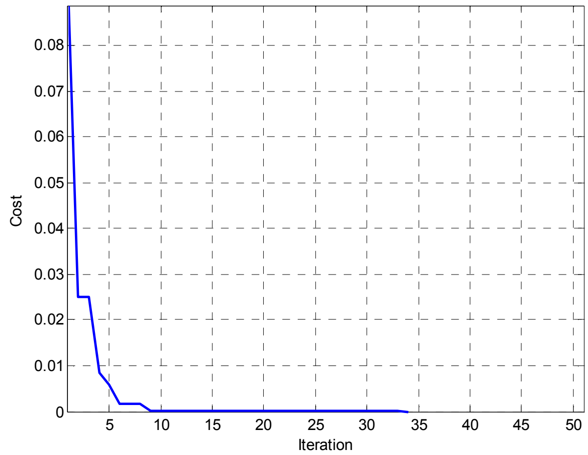

Fig. 10. Convergence of GA for ANN (f_d =6 GHz)

GA converged at the 33th iteration. Elapsed time during optimization is 7.37 sec. Obtained L and W values via optimization for f_d =6 GHz are L=9.8911mm and W=12.5233 mm. $|S_{11}|$ graph of HFSS simulation is given in Fig. 11. Resonant frequency for the same L and W is obtained as 5.7 GHz in HFSS. Error between resonant frequencies of simulation and optimization is 5%.

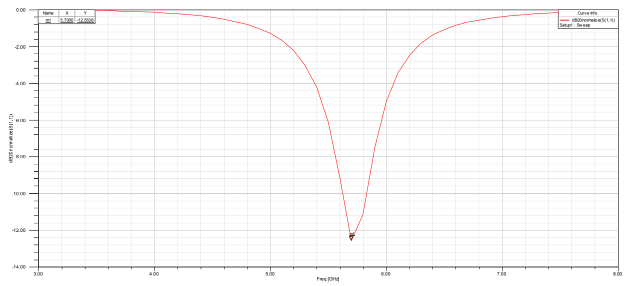

Fig. 11. $|S_{11}|$ value for f_d =6 GHz with L=9.8911 mm and W=12.5233 mm

As another example of ANN trained optimization, desired resonant frequency f_d is selected as 6.5 GHz. Cost function values with respect to iteration number for 6.5 GHz are given in Fig. 12.

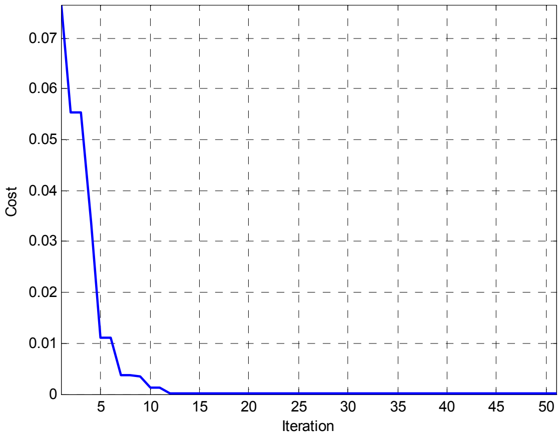

Fig. 12. Convergence of GA for ANN (f_d =6.5GHz)

In this case, GA could not converge and the maximum number of iterations was reached with an error. Elapsed time during optimization is 8.07 sec. Obtained L and W values via optimization for f_d =6.5GHz are L=9.8877 mm and W=14.7585 mm $|S_{11}|$ graph of HFSS simulation is given in Fig. 13. Resonant frequency for the same L and W is obtained as 6.3 GHz in HFSS. Error between resonant frequencies of simulation and optimization is 3.07%.

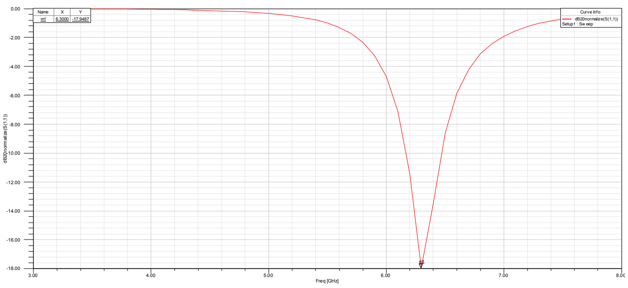

Fig. 13. $|S_{11}|$ value for f_d =6.5 GHz with L=9.8877 mm and W=14.7585 mm

6. Conclusion

In this work, Genetic Algorithm (GA) optimizes models obtained by Support Vector Regression (SVR) and Artificial Neural Network (ANN) to obtain desired resonant frequency of a conformal antenna. Firstly, to show superiority of SVR over ANN, a pattern obtained by HFSS simulation has been trained and tested with ANN and SVR. Training time and error of SVR are observed to be less then ANN's.

Antenna geometric variables (L and W) obtained by GA are used for HFSS simulation and the results obtained by the proposed approach and HFSS have been compared.

It has also been observed that GA optimization with SVR model gives the results more quickly and accurately than GA optimization with ANN.

7. References

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