PSO driven RBFNN for design of equilateral triangular microstrip patch antenna

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Recent advances in computer aided design packages for electromagnetic applications have helped antenna engineers to design, simulate and synthesize antennas efficiently. The PSO driven RBFNN has been developed to calculate the resonant frequency of equilateral triangular microstrip patch antenna (ETMPA). The present paper highlights the simplicity, computational efficiency and accuracy of the proposed method. The achieved results have been compared with published experimental and theoretical findings to validate the presented approach, which seems to be in very good agreements.

Keywords: Particle swarm optimization (PSO), Radial basis neural network (RBFNN), Artificial neural network (ANN), PSO driven RBFNN, Equilateral triangular microstrip patch antenna (ETMPA)

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1 Introduction

Microstrip antennas are finding growing interest in space, radar, wireless and bio-medical applications due to their attractive features like ease of fabrication, light weight and compatibility¹. These features make the planner antenna more attractive in the present emerging scenario like MIMO systems²-³. As the demand is growing day by day for miniaturization and efficiency, the challenge for development of accurate and efficient tools for precision design is also growing. In the present paper, a particle swarm optimization⁴ driven radial basis neural network⁵-⁶ (PSO driven RBFNN) is proposed to calculate accurately and efficiently resonant frequency of equilateral triangular microstrip patch antenna (ETMPA). The presented hybrid tool of PSO and RBFNN seems to be a good computer aided design (CAD) tool for planar antenna design.

2 Formulation of PSO-RBFNN system

PSO has been successfully applied in many areas, like function-optimization in electromagnetic field, artificial neural network training, fuzzy system control and other areas where genetic algorithm (GA) are generally applied⁵-⁶. The PSO optimization process finds local best (lbest) and global best (gbest) by mechanism of displacement and velocity of particles⁷-⁸. The particle displacement and the particle velocity are expressed as⁷:

\[ S(t) = S(t-1) + V(t) \] … (1)

\[ V(t) = W^* V(t-1) + C_1 r_1 (lbest - S(t-1)) + C_2 r_2 (gbest - S(t-1)) \] … (2)

where, \( V(t) \) is particle velocity; \( S(t) \) particle displacement; lbest, local best; gbest, global best; \( W^* \), inertial weight; \( C_1 \) and \( C_2 \), acceleration constants; \( r_1 \) and \( r_2 \), random values; and \( t \), current iteration.

To get the solution (gbest), initially the particles are allowed to move randomly in N-dimensional coordinate space. The evolutions of particles are guided only by the best solution and tend to be regulated by behavior of the neighbors. In the simplest form, this evolutionary procedure can be represented by position and velocity of particles expressed in Eqs (1) and (2), respectively. RBFNN as in Fig. 1 are applied for various modeling purposes⁵. In RBFNN, the inputs \( x \), the total input to the \( i^{th} \) hidden neuron \( (h_i) \) is expressed as⁶:

\[ h_{ij} = \sqrt{\sum_{j=1}^{n} \left( \frac{x_j - c_{ij}}{\lambda_{ij}} \right)^2} , i = 1, 2, ..., N \] … (3)

where, \( N \), is number of hidden neurons; \( z_{ij} = \sigma(h_i) \), output value of the \( i^{th} \) hidden neuron; \( \sigma \), a radial basis function. The parameters \( c_{ij} \) and \( \lambda_{ij} \) are centres and...
standard deviations of radial basis activation functions. Finally, the outputs of the RBF network are computed from hidden neurons as:

\[ y_k = \sum_{i=0}^{N} W_{ki} z_{ki} \]  

...(4)

where, \( W_{ki} \) is the weight of the link between the \( i^{th} \) neuron of the hidden layer and the \( k^{th} \) neuron of the output layer. Training parameters ‘W’ of the RBF network include \( W_{ki}, c_{ij}, \lambda_{ij}, k = 1, 2 \ldots m; i = 1, 2, \ldots N; j = 1, 2 \ldots n \).

In the proposed method, the weight of neural network is replaced by particle position equation and the rate of change, i.e. \( \frac{\partial E(t)}{\partial W(t)} \) of the neural network is replaced with particle velocity expression.

PSO driven RBFNN is proposed to calculate resonant frequency of equilateral triangular microstrip patch antenna. The mean square error (MSE) is used as the fitness function which is represented as:

\[ \text{MSE} = \frac{1}{N_p} \text{(target-output)}^2 \]  

...(5)

where, \( N_p \) is the number of patterns.

The PSO is used to minimize the error between input and output of RBFNN by updating the weight between input to hidden layer and hidden to output layer neurons. The radial basis function is used as activation function at hidden layer. The performance of PSO driven RBFNN is evaluated by taking training, testing and evaluating patterns of various design antennas. The parameters of PSO driven RBFNN are as follows:

- Number of input nodes = 5;
- Number of hidden nodes = 10;
- Number of output nodes = 1;
- Number of weights between input and hidden layer = 50;
- Number of weights between hidden and output layer = 10;
- Activation function at hidden layer output is radial basis function;
- Activation function at output layer output is linear activation function;
- Fitness function is mean square error;
- \( C_1 = C_2 = 2; \)
- \( r_1, r_2 = \text{random} \ [0 \ 1]; \)
- \( W = 0.9 \text{ to } 0.4; \)
- Number particles = 25;
- Maximum particle velocity = 5;
- Number of iterations of PSO = 50;
- Number of epochs of ANN = 450.

The pseudo code of PSO driven RBFNN is presented as follows:

Step 1: Initialize particle position and velocity at random.
Step 2: Evaluate fitness function.
Step 3: Update the weights, lbest and gbest.
Step 4: If the error is 0.001 go to Step 2 else continue.
Step 5: Update gbest.
Step 6: If no. of particles is equal to 25 go to Step 2 else continue.
Step 7: If number of iterations is not equal to zero then go to Step 2 else continue.
Step 8: End.
Step 9: After the evolutionary process, train the best network further with PSO algorithm on the combined training and validation set until it converges.
Step 10: Repeat next iteration.

3 Implementation of the model

In the paper, the resonant frequency (fr) of equilateral triangular microstrip patch antenna is calculated using its parameters like patch length (a), permittivity of the substrate (\( \varepsilon_r \)), height (h) of the

Fig. 1 — RBF neural network structure
substrate and modes $TM_{m,n,l}$ (refs 7-8) as shown in the geometric of equilateral triangular microstrip patch antenna (Fig. 2).

The resonant frequency of equilateral triangular microstrip patch antenna is expressed as:

$$f_{m,n,l} = \frac{2C}{3\alpha_{\text{eff}} (\varepsilon_r)^{\frac{1}{2}}} \left( m^2 + mn + n^2 \right)^{\frac{1}{2}}$$  \ldots (6)

where,

$$\alpha_{\text{eff}} = a \left[ 1 + \frac{2h}{\pi \varepsilon_r a} \left( \ln \left( \frac{\pi a}{2h} \right) + 1.7726 \right) \right]^{\frac{1}{2}}$$  \ldots (7)

For feed forward neural network, resonant frequency ($f_{m,n,l}$), permittivity of the substrate ($\varepsilon_r$), height ($h$) of the substrate and modes $TM_{m,n,l}$ are taken as inputs where resonant frequency of ETMPA is taken as output in RBF neural network of 5-10-1 (Fig. 3).

Twenty-nine patterns from refs (10-13) are taken for training the networks and rest four patterns are used for testing the networks. Table 1 shows the comparison between experimental results with GA and PSO-RBFNN. Table 2 presents comparison of PSO, artificial neural network (ANN) (ref. 4) and PSO-RBFNN methods. As seen from Table 2, the PSO-RBFNN fused soft computing tool is computationally efficient and provides better accuracy and hence can be suitable soft computing tools for the situation like whole body simulation, array of antenna embedded on the body of missiles, etc. The algorithm was applied for present work for microstrip antenna on thick substrate, i.e. $h/\lambda_0 > 0.0815$ for which the standard formula available in literature fails to provide accurate results. The paper aims at drawing the attentions to the process of information fusion and their applications to efficient antenna design. Simple antenna structure is considered to test the success of the proposed method. The developed code is being used to analyze and optimize the parameter of parasitically coupled stacked microstrip patch antenna and large uniform and non-uniform array. The simulated results will be compared with experimental finding and published in future. For multilayer structure like stacked patches, proposed algorithm is found to be quite efficient. Number of layers,
substrate thickness, gap spacing between substrate and overall dimension of different substrate layers are included as part of the input parameters to PSO-RBFNN. The resonant frequencies are obtained for triangular and rectangular microstrip antenna. An error of 4.6% is observed and the efforts are being made to reduce it. Figure 4 depicts the comparison of convergence. As seen from Table 2, the error in the proposed method is less than 0.01%.

4 Conclusion

A novel approach to determine resonant frequency of equilateral triangular microstrip patch antenna using PSO-RBFNN technique is developed and presented. The proposed method could achieve better accuracy and with reduced computational time. The proposed method may be used as an alternate CAD simulation tool for microstrip antenna design due to its simple and generalization characteristics. The presented method can be used in the design of miniaturized antenna with and without loading. The proposed method can be used for multi-stacked patch antenna and for large antenna array design.

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References


