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Hpnna Based Fss Designing: A Case Study

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Abstract —Soft computing exploits the biological processes to simplify scientific and technical problems. Correspondingly, soft computing is employed in Frequency Selective Surface designing. In this particular endeavor a Back Propagation Algorithm trained Artificial Neural Network is reported for the designing of single layer Frequency Selective Surface. The prime aspiration was to ascertain the Resonant Frequency and the Band Width of a crossed dipole Frequency Selective Surface. In due course of action and to attain maximized throughput latterly a hybrid Particle Swarm Optimization trained Artificial Neural Network is formulated. The empirical study confirmed that Hybrid Particle Swarm Optimization trained Artificial Neural Network is amply efficient and effective for global and fast local searching procedures. Afterward a comparative analysis of Hybrid Particle Swarm Optimization and Back Propagation Algorithm is contemplated.

Keywords— ANN, FSS, BPA, HPNNA, PSO

I. INTRODUCTION

Frequency Selective Surface (FSS) proliferated since the last three decades. Study on FSS acclimatized both in industry and academia as it rendered brilliant applications in contemporary communication engineering. Incorporation of FSS in wireless devices has been empirically demonstrated by B Munk [1]. Its applicability is amplified in a military application for their radar system and this has lead to the inclusion of FSS in wireless devices, WLAN Router [2] and other electronic communication technology [3]. It can be aptly anticipated that FSS is not limited to wireless communication engineering. It is also used in smart buildings. Kiyani et. al. demonstrated the use of FSS to reduce thermal effect in Smart Building[4]. Choi et. al incorporated FSS as water Bolous for microwave medical applications [5]. Such vivid orientation of FSS application has motivated scientists and researchers to deeply study the characteristic of FSS. It yielded that FSS are either inductive or capacitive. The inductive FSS acts as a transmitter and capacitive FSS are simply reflector [6].

In order to attain maximum throughput, it is earnestly required to obtain parametric extraction of BandWidth (BW) and Resonant Frequency of different FSS structures. In this regard different commercial software like ANSOFT, FEKO is improvised based upon Method of Moment (MOM), Finite Element Method (FEM) etc. But unfortunately, all such reported commercial software is largely time-consuming. Thus urgency for better methodological research was sought. Incorporation of soft computing tool in this regard is presently considered as a primary solution. Several research articles have been reported in this regard [7]. The authors already articulated parameter extraction of Resonant Frequency and periodicity using soft computing tools like Artificial Neural Network (ANN), Particle Swarm Optimization (PSO) in the reputed journals [8, 9]. Even in their very recent research effort, they reported one Hybrid Particle Swarm Optimization trained Artificial Neural Network Algorithm (HPNNA).

Here the objective of authors is to use soft computing tool for parametric extraction in an efficient way in order to reduce the computational time as well as lessen the error. In other words, HPNNA is introduced to achieve greater performance in FSS designing for parametric Extraction.

Section II enumerates the design strategy of FSS whereas section III deliberately focus on the basic challenges of FSS designing. Section IV and V is a study of PSO and ANN from FSS design perspective. Subsequently, Section VI and VII introduces BPA and HPNNA in FSS designing. Lastly, the comparative result analysis is presented in an ephemeral way in Section VIII.

II. FSS DESIGN PERSPECTIVE

The notion of FSS design involves several conceptual implementations of parameter ranging from material to different shapes of patches. Other considerable factors are dielectric width and periodicity. Keeping pace with all such necessities the authors in this manuscript propose an FSS model whose parameter values are tabulated in Table-1.

Structurally, the unit cell is a 10X10 mm² crossed dipole framework and the having permeability of 4.4 is used for particular FSS design. The copper is used in the design patches for particular FSS. The authors without confining themselves in only hardware modeling of FSS, put a leap forward to include soft computation in FSS research vicinity. Regarding this MOM based ANSOFT simulator is incorporated to simulate the proposed FSS. Accordingly, a minimum of 250 simulation dataset is generated for training the ANN model and it is programmed using MATLAB. Results obtained from ANN model is compared with the ANSOFT simulated result. Figure -1 depicts the proposed unit cell structure with a periodicity of 17X17 mm².



Figure 1.Proposed unit cell structure Table 1: FSS parameters considered in this study designing of cross dipole FSS structure

FSS	Parameter value
parameter	
X-direction	T _X
periodicity	= [11, 11.5, 12, 12.5, 13, 13.5, 14, 14.5, 15,
	15.5,16,16.5,17,17.5,18,18.5,19,19.5,20]
	all are in mm.
Y-direction	T _Y
periodicity	= [11, 11.5, 12, 12.5, 13, 13.5, 14, 14.5, 15,
	15.5,16,16.5,17,17.5,18,18.5,19,19.5,20]
	all are in mm.
The width	1.6mm
of the	
dielectric	
Substrate	4.4
relative	
permeability	

III. PROBLEM DEFINITION

Numerous research attempts have been reported so far in specific FSS design [1]. Contemporary research initiatives have already crossed the barriers of traditional hardware FSS modeling. Concurrently, soft computation evolved in FSS modeling and new research challenges are met. One such

Vol.6(5), May 2018, E-ISSN: 2347-2693

fascinating but challenging endeavor is to obtain least error BW and Resonant Frequency for the particular FSS considered herein. The authors in this connection studied the proposed FSS model through ANN structure. The ANN configuration is shown in Figure-2, where the periodicity in X-direction and Y-direction are used as the input to the ANN model and output for the ANN model is Resonant Frequency and BW respectively. It is a 2X3X3X2 ANN model. This structure is simulated for at least 250 data set. Output result for the proposed model is compared with ANN trained by Back Propagation Algorithm (BPA) and HPNNA model. Later on, to obtain the best result for least error Resonant Frequency and BW, the author relied upon comparing on BPA and HPNNA technique. Lastly, the output is evaluated to meet the stipulated Resonant Frequency and BW. In other words, the authors wished to develop a relied strategy to obtain least error Resonant Frequency and BW within the shorter time span and least computational complexity.



Figure2.Proposed ANN model for prediction of Resonant Frequency and Band Width.

IV. PARTICLE SWARM OPTIMIZATION:

Particle Swarm Optimization (PSO) is a stochastic population-based search process involving the social conduct of animals like fish and bird. James Kennedy and Russel Elbert primarily conceptualized PSO algorithm in 1995[10]. In search space, each individual solution is known as a particle. As per the strategy of PSO, all particles need to alter its position bestowing its experience and its neighboring solution. Searching of the best solution starts initially in a random manner. The particle can start flying fast and far from the best solution to explore in a random manner which is termed as global search. It can fly very slowly and close to a particular solution i.e. best solution for final tuning. Regardless to say that the PSO is a simplistic and easily implemented global searching algorithm. Position and velocity expression can be updated by using following equation 1 and 2.

 $V_{(l)}(i+1) = WV_l(i) + C_1R_1(P_i - X_i) + C_2R_2(P_g - X_i)$ (1) $X_{(l)}(i+1) = X_l(i) + V_l(i+1)....(2)$

Where V_i and X_i denotes velocity and position vectors of particle i respectively. The finest position of the particle is denoted by P_g . P_i is the local best position for the ith particle. Learning factor is denoted by C_1 and C_2 . Inertia weight is represented by W. Besides, the R_1 and R_2 are random variables used for providing the stochastic aspect. For reducing the search space by increasing the iteration W is changed as follows

V. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is quite analogous to a simple human nervous system [11]. Basically, it comprises of neuron and link. A neuron is the processing element and link is used for connection of two neurons through different weight parameters. Every neuron receives information from other neurons and processes the information to produce output using activation function. The first and the last layer of ANN model is known as input and output layer. Amid this input and output layer exist a middle layer which is known as a hidden layer. The function of the input layer is to buffer data into the network. But the input layer does not contain any weight and activation function. Even the hidden layer does not have any connection to the outside world. The output layer provides the output data for the corresponding given input. The proposed ANN model is shown in figure-2. The neural network is shown in figure-2 and can be expressed using equation (3 and 4).

$$\begin{split} h_{oi} &= f \Big(\sum_{j=1}^{R} i w_{i,j} x_j + h b_i \Big)(4) \\ \text{for } i = 1N \\ y_i &= f \Big(\sum_{k=1}^{N} h w_{ik} h_{ok} + o b_i \Big)(5) \\ \text{for } i = 1S \end{split}$$

Where R, N, S are the number of input, hidden neurons and output respectively. 'iw' and 'hw' are the hidden weight matrix. hb and ob are the bias vector for hidden layer and output layer respectively. Hidden layer output is represented by h_o and y is the final output layer. An ANN is not a self-sufficient computational tool as it requires different training algorithm. One such training algorithm is BPA.

VI. ANN TRAINED BY BACK PROPAGATION Algorithm (BPA)

Back Propagation Algorithm (BPA) is a commonly used algorithm for supervised learning process [11]. It is a classical domain dependent technique. It works on the basis of output error measurement. For weight training procedure error gradient direction is used. BPA basically finds the local optimum value. The Mean Square Error (MSE) is used for fitness function and it can be defined by

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Where d_i is actual desired output value and f_i is the output calculated by ANN model.

For weight adjustment generally, equation 6 is used.

$$\Delta w_{t} = \eta \nabla_{w} E(w_{t}) \dots (7)$$

Where η is the learning rate.

Yet the fragility of BPA exists. Empirical study revealed that BPA is best suited to obtain the local search optima but it shows no benevolence for global search optima. This leads to computational deficiency. The author hereby acknowledges the shortcomings of BPA and subsequently adhere to PSO algorithm which shows comparatively reliable global search optima but again the local search optima are somehow compromised. In order to restore maximum flexibility both for local search optima as well as for global search optima the authors in their earlier attempts hybridized BPA and PSO. Thereby a new algorithm for FSS design based on ANN is envisaged namely HPNNA.

VII. HYBRID PARTICLE SWARM OPTIMIZATION TRAINED ARTIFICIAL NEURAL NETWORK ALGORITHM (HPNNA)

The course of action is initiated by hybridizing PSO along with most familiar ANN. The ANN weight is basically trained by Gradient Decent method. Most of the research endeavor is quite fascinating but one has to keep in mind that BPA is a local search algorithm. Hence the maximum throughput is somehow limited. In order to achieve the highest potential, PSO and BPA are amalgamated; the result of which resolved both local and global search problems [12]. Sequentially PSO is initiated and is followed by BPA to achieve faster movement of training. It is evident that the fitness function value remains unchanged for few generations. Later on, gradient searching method is employed to avail best searching value. It is crystal clear that this algorithm is independent of "structure of ANN model". Hence it stands to be fit for prediction of Rf and BW of the proposed FSS structure as well as any FSS structure. Last but not least, the Root Mean Square Error is formulated similarly to the equation 7; it is the basic criterion of the said prediction parameter.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\text{atop}_n^a - \text{prop}_n^f)^2} \dots \dots \dots (7)$$

Where $atop_n^a$ is the output obtained by simulation and $prop_n^f$ is the predicted output frequency value. Flowchart used for HPNNA implementation shown in figure 3.



Figure 3. Flowchart used in HPNNA training method

VIII. RESULT AND DISCUSSION

The prime focus of this research attempt remains centrifugal towards obtaining Resonant Frequency and BW with minimum error. BPA and HPNNA are consecutively introduced in the ANN modeling for FSS design. Subsequently, the obtained results are compared to MOM based ANSOFT simulation result. The entire results are tabulated in table 2, 3, 4. Table 2 represents the input sequence used in ANN training. Table 3 represents the corresponding output obtained by MOM simulation in ANSOFT. Table 4 represents output obtained by BPA and HPNNA training method.

Now analyzing both BPA and HPNNA it is revealed that BPA based result is highly erroneous for the case of bandwidth when compared to its HPNNA counterpart. On the other hand, if the MOM based results and HPNNA based results are compared it is evident that HPNNA oriented results are significantly more effective as well as the time consumed by both Resonant Frequency and BW is much low for HPNNA. Last but not least, the correlation parametric values are compared with MOM based ANSOFT result in Table-5 herein under which it is clearly depicted that HPNNA is a more promising candidate compared to BPA in future FSS design. Table-2 Input Data for the predicted result for ResonantFrequency and BW using BPA and HPNNA

Sl.	Input Data		
No	X-direction periodicity (mm)	Y-direction periodicity (mm)	
1	12	15	
2	14	12	
3	17	17	
4	15	17	
5	18	19	

MOM		
Resonant Frequency GHz	BW GHz	
8.84	1.13	
8.79	0.88	
8.94	0.46	
9.16	0.56	
8.89	0.38	

Table-4 Output Data for the Predicted result for Resonant Frequency and BW using BPA and HPNNA

sl. No.	Out Put Data			
	BPA		HPNNA	
	Resonant	BW	Resonant	BW
	Frequency		Frequency	
	GHz	GHz		GHz
			GHz	
1	8.79	0.99	8.83	1.11
2	8.75	0.76	8.80	0.86
3	8.89	0.38	8.95	0.47
4	9.12	0.47	9.17	0.55
5	8.82	0.29	8.9	0.39

Table-5 Correlation between BPA and HPNNA results with MOM method (BW prediction)

BPA	HPNNA	
0.95	1	

IX. CONCLUSION

Ample study of table 4 and 5 with respect to MOM based ANSOFT simulation result (Table 3) is articulated here. The

impact of HPNNA based prediction for Resonant Frequency and BW for one particular FSS is successfully detailed in an ephemeral way. For better clarity X and Y-direction periodicity is taken multiple times in cross dipole FSS structure. Unambiguously it can be stated that both the BPA and HPNNA oriented result are in good agreement with MOM based simulation result. Furthermore, HPNNA shows excellent figure merit compare to BPA as revealed in Table-3. Thus, prediction of Resonant Frequency and BW, with different weight training methods are proposed using an ANN modeling and HPNNA stands to be a most effective algorithm in designing FSS. Also, a new trend is probably set to explore HPNNA based ANN modeling for different structures of FSS designing and this can be further extended up to curved FSS in near future. Besides a thorough insight ensure that HPNNA being a structure independent algorithm fits well when weighted against BPA counterpart.

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