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Neural Network Approach for Resonance Frequency Estimation of Aperture-Coupled Microstrip Antennas

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ABSTRACT

In this study, the simulation model of Aperture-Coupled Micro-Strip Antenna (ACMA) by using Artificial Neural Network (ANN) is proposed. The developed model tries to predict the output resonance frequency of the ACMA according to the input physical parameters of the antenna. ACMA models were designed in High Frequency Structure Simulator (HFSS) software tool that could conduct three dimensional full-wave electromagnetic structure analysis based on Finite Element Method. Main objective is to simulate HFSS model via proposed learning model. Levenberg-Marquardt (LM) is utilized as a learning algorithm. 500 different ACMA models was designed in HFSS tool. Physical dimensions and output operating frequencies of the ACMA models were recorded in order to establish the dataset. Prediction performance of the proposed ANN simulation model was evaluated by 5-fold cross-validation scheme. Overall generalization error was calculated as 3.58 %. Experiments revealed that proposed simulation model operates at least ten thousand times faster than HFSS software. Due to its overwhelming running speed, it was concluded that proposed LM-ANN simulation model can be utilized as a preliminary search tool for optimizing the industrial ACMA models.

KEYWORDS: Prediction model; aperture coupled microstrip antenna; artificial neural network; resonance frequency.

INTRODUCTION

With the latest development in modern communications technology, the demand for wireless applications has increased, raising the significance of integrated and high-gain antenna design. Microstrip antennas (MA), used in several applications such as wireless network services, satellite and rocket navigation, radar systems, and in the biomedical field, have shown their efficiency and usability among the type of antennas [1]. With its disadvantages such as low-gain and narrow bandwidths, MA has been the subject of research for improvement in these areas via selection of special non-conductor materials and modification of geometrical structures. There are several methods used to compare the MA performances. MAs that exhibit structural differences could be analyzed in two groups. In addition to the gap model [2] and transmission line model [3] in uniform MA analysis, one of these structure is ACMA feeding technique in non-uniform MA structures; full-wave model techniques are utilized [4], however the analysis process is complicated. The desired output parameters for the complex, and time-consuming antenna structures are calculated by long analyses and design cycles [5]. One of these analysis processes is the HFSS [6] software. HFSS software package is a high performance full-wave electromagnetic (EM) field simulator that utilizes Windows® graphical user interface. While simulation of antenna prototypes designed in HFSS environment would provide advantages in eliminating unnecessary costs in fabrication phase, its physical analysis capabilities are limited due to the complexity of a highly accurate full-wave model in the background. Furthermore, due to the high calculation load created by simulation programs utilized to get the desired antenna parameters, the results are obtained after a long period of time, and thus led to a search for new computer-aided methods. Machine learning algorithms can learn the underlying function via data driven fashion. One of these methods was ANN. ANNs became popular during the recent years due to their fast learning skills, easy adaptability for different problems, generalizing capability, and efficiency with little data [7]. Today, neural network models resolve the problems in calculation of the characteristic parameters of MAs, created by the complex and time consuming mathematical methods in many studies [8].

In this study, Levenberg-Marquardt Artificial Neural Network (LM-ANN) simulation model is proposed to predict output resonant frequency of ACMA, which depends on geometric shape values including patch length, patch width, feed length, aperture width and aperture height. Prediction performance of the LM-ANN is evaluated by 5-Fold cross-validation (CV) technique. Another concern is related to exhibit running speed of the proposed simulation model.

MATERIALS AND METHODS

Microstrip Antenna Design

Electrical and physical structure of the ACMA is presented in Figure 1. ACMA consists of two layers separated by a ground surface. Upper insulator includes the ε_r permission element, and the lower insulator includes the ε_{rf} micro-strip feed line. A tiny cut on the ground surface enables the connection to the emitting patch from the open-circuit micro-strip feeding line. Output parameters of the antenna, shape and dimensions of the emitting patch, dimensions of the ground surface, dimensions of the aperture, and position and dimensions of the feeding line are dependent on the dielectric constants of the two material [9].

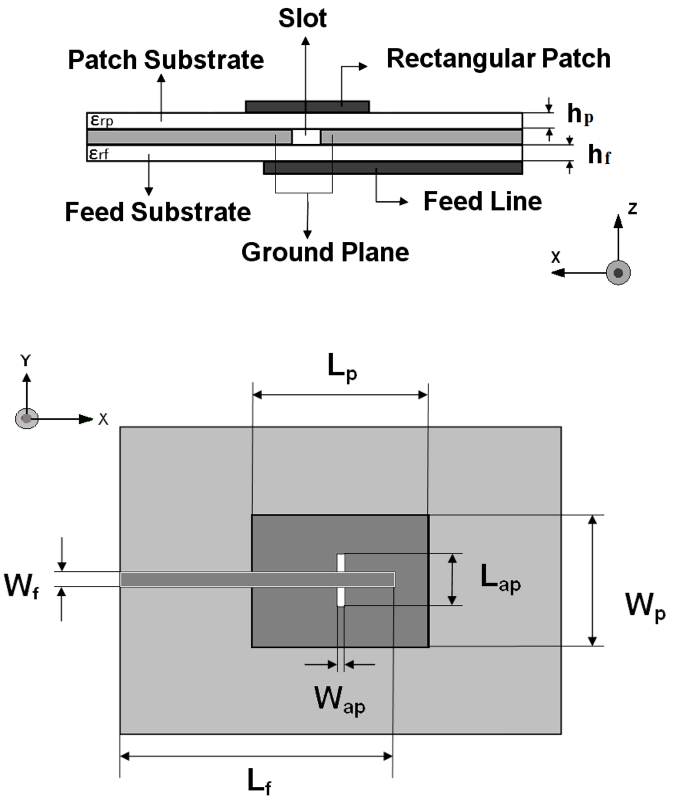


Figure 1. Side (top) and top (bottom) views of the ACMA.

Antenna parameters used for the ACMA design in Figure 1 are as follows:

- Patch dimensions
  - L_p: length of the patch
  - W_p: width of the patch
- Aperture dimensions:
  - L_{ap}: length of the aperture
  - W_{ap}: width of the aperture
- Feed dimensions:
  - L_f: length of the feed line
  - W_f: width of the feed line

Operation theory of the ACMA is presented in Figure 2 as well. Feeding line creates the electrical field through the aperture (small opening cut on the ground surface) of the surface currents formed on the patch. Sides of the patch, which is perpendicular to the feeding line, generate unwanted fringe currents in the free space [10]. Rectangular patch defines the area of radiation. The aperture is utilized to reduce cross polarization that occurs due to the symmetrical structure. Feeding line is used to prevent unwanted emissions and to regulate the performance.

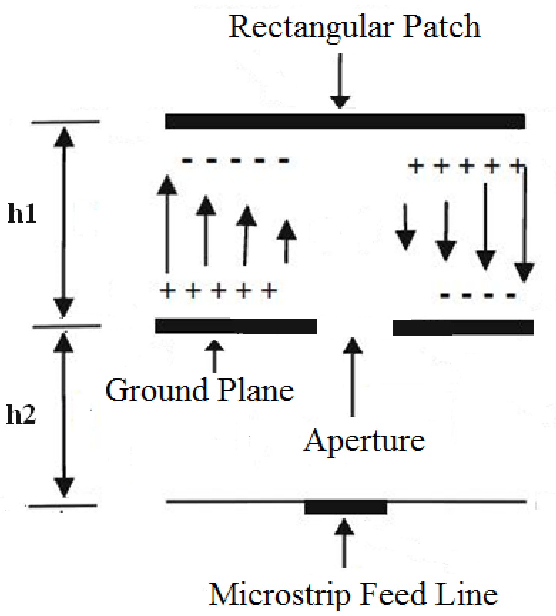


Figure 2. Basics of the aperture coupled microstrip antenna [10]

The radiating patch and the aperture are usually designed in rectangular form. The geometrical shape of the ACMA modeled by HFSS software, which is used to simulate and design three dimensional full-wave electromagnetic structures, is shown in Figure 3.

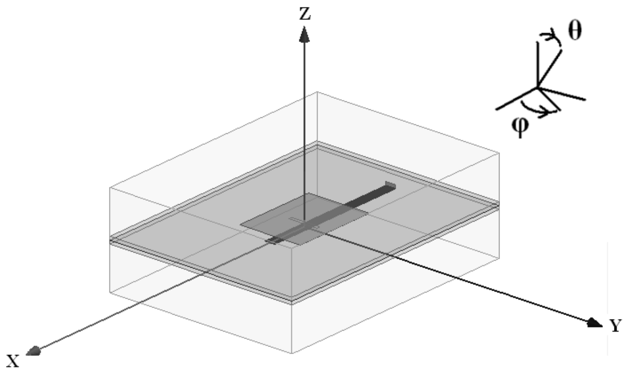


Figure 3. HFSS model of ACMA

Dataset Generation

The dataset of this study consists of 500 samples produced by using HFFS software [11]. Each sample in the dataset includes 5 ACMA input parameters (L_p, W_p, L_{ap}, W_{ap}, L_f) and one output resonance frequency (f_r) value. General view of the simulation process is illustrated in Figure 4. Dielectric constants for both dielectric materials used in ACMA were $\boldsymbol{\varepsilon_r}$= 2.2. Since the dielectric material was easy to use and dielectric loss tangent was 0.0009 dB, Rogers RT/duroid 5880™ dielectric material was preferred.

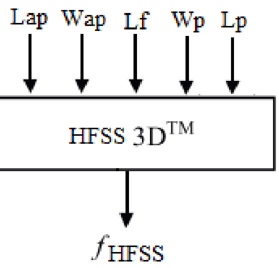


Figure 4. Proposed simulation model

In datasets, ACMA geometrical parameters were taken into consideration, however electrical parameter ε_r was excluded in the datasets. Dielectric constant and the thickness of the utilized dielectric material were kept constant. Certain output resonance frequency values that correspond to ACMA input parameters used in HFSS are listed in Table 1. An ANN model based on Multilayer Perceptron (MLP) was developed in this study to calculate ACMA resonance frequency. MLP was used to model the relationship between the simulated antenna parameters such as patch dimensions of the antenna, dimensions of the aperture area, and the feed strip length, and corresponding resonance frequency values.

Table 1. First five rows of the dataset generated by HFSS software.

Model Number	Input Parameters					Output Parameter
	Lp (cm)	Wp (cm)	Lap (cm)	Wap (cm)	Lf (cm)	fr (GHz)
1	4.446	3.602	0.203	1.371	6.948	1.950
2	3.977	3.123	0.197	1.656	6.164	2.090
3	3.838	3.415	0.164	1.895	5.786	2.190
4	3.010	3.639	0.160	1.836	5.396	2.500
5	2.513	2.648	0.201	1.162	6.225	3.110

Neural Network Modeling

Several different structures exist for ANNs. MLP that are successfully used in many engineering problems were preferred in this study [12]. Similarly, different algorithms such as LM, back-propagation and delta-bar-delta are used for MLP training. In this study, MLP was trained using LM algorithm, which has properties such as fast learning and good convergence [13, 14]. MLP includes three layers of input, output and hidden layers as displayed in Figure 5.

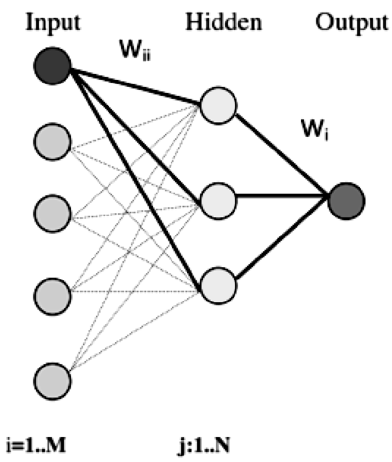


Figure 5. Basic structure of the MLP model

Neurons of the input layer behave as a buffer to distribute the X_i input signals to the neurons of the hidden layer. Each j neuron in the hidden layer collects the input X_i signals by first weighting them via the power of W_{ji} connections and calculates the y_j output as the total f activation function. Activation function could be a simple and differentiable threshold function such as sigmoid, hyperbolic tangent, radial based and a pure linear function, etc. [15]. The output of the neurons in the output layer are calculated similarly. Activation function can be expressed as below:

$$y_i = f(\sum w_{ji} x_i) \qquad (1)$$

In this study, proposed ANN model and evaluation algorithms were implemented with GNU Octave software [16]. Three-layered ANN architecture was adapted in the study. Since the increase in complexity in architectures larger than three layers require an exponential increase in learning data, the simplest architecture of a single hidden layer architecture was preferred. The number of geometrical parameters that would be used in ACMA design identifies the number of neurons in input layer, and the number of resonance frequencies identifies the number of neurons in the output layer. L_p, W_p, L_{ap}, W_{ap}, and L_f were used as input parameters in the ANN model. The output parameter was the resonance frequency, f_r. As a result of the experiments conducted, it was determined that the most appropriate ANN topology was 5-neuron input layer, 8-neuron hidden layer, and 1-neuron output layer model [11].

Proposed ANN model is presented in Figure 6. Input neurons L_p, W_p, L_{ap}, W_{ap}, L_f in the input layer displayed in Figure 6 correspond the input parameters given in Table 1. Gray neurons in the middle represent hidden layer neurons, f_r represents the output neuron in the output layer, total of which correspond to the output parameter displayed in Table 1.

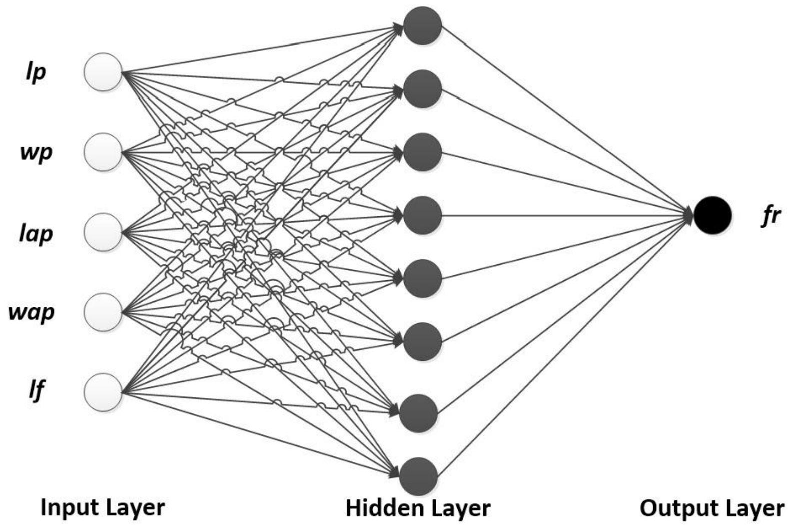


Figure 6. Topology of the proposed ANN model.

Initial connection weights and bias values were generated by random function. As a result of several tests conducted during the study, both the most suitable number of neurons in the hidden layer and the values of free parameters of the ANN were updated to generate the smallest test error, and the most appropriate learning coefficient was set and fixed to 0.3, training epoch number to 150 and the number of neurons in the hidden layer to 8.

Developed ANN model was trained using the samples generated by HFSS. Hyperbolic tangent sigmoid function was utilized as a transfer function for the hidden ANN layer, while linear function was utilized in the output layer as a transfer function. During training, input samples are utilized successfully in the input layer of the neural net and synaptic weights are modified to arrive at the desired output responses. Since the training errors were minimized around 100-150 epochs, training process was terminated. Afterwards, the accuracy of the trained neural net was tested using a test dataset that it did not encounter during training.

In data mining and machine learning applications K-fold cross validation method with K is chosen as 5 or 10 in most studies [17, 18]. General approach for the determination of K is related to the volume of the dataset. For relatively small dataset K value becomes greater in order to enable the classifiers to have maximum benefits from the dataset in the learning process [18]. In this study, the accuracy of the developed ANN model was evaluated with 5-fold cross validation. 5-fold cross validation works as follows: First dataset is shuffled then, it is divided into five equal parts. Training is performed on 4 parts and remaining part is used for testing issue. Each part is used as a test set for each validation. For this reason this operation is called as cross-validation. This process is repeated five times so that each part is used once as the test dataset. Finally, the mean of five different accuracy values were taken. This method is widely used in machine learning applications due to its minimum bias to the data in the dataset [19]. Percentage error formula as a generalization performance metric is expressed as below:

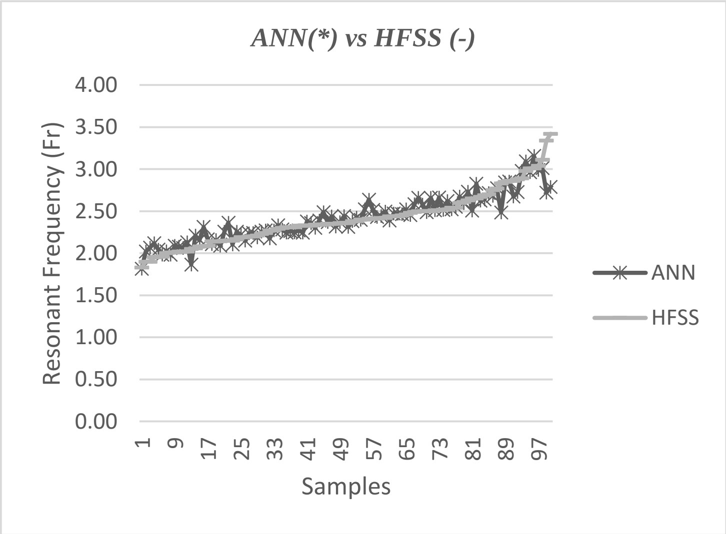
$$\% \text{ Error} = \left|\frac{fr(HFSS) - fr(ANN)}{fr(HFSS)}\right| x\ 100 \qquad (2)$$

RESULTS AND DISCUSSION

The study was conducted on a computer with an Intel Pentium i5-1.80 GHz processor, 8 GB memory, and Windows 7 operating system. A portion of the input parameters and results obtained from ANN model and HFSS are displayed in Table 2, where it could be observed that the frequency values were in accordance. As a result of 5-fold cross validation, mean test error and standard deviation of mean error were calculated as 3.58% and 0.0495, respectively. Correlation Coefficient (R) values of validation and test set were 0.91 and 0.90. Figure 8 presents overall prediction performance of ANN model as two different graphics. Note that in Figure 7, frequency values of HFSS were sorted so that prediction performance of the proposed learning models can be well expressed. It could be observed that obtained ANN results were highly compatible with the HFSS results.

Table 2. Input parameters and % Error rates of both HFSS and proposed ANN Models.

	Input Parameters					Output Parameters		
	L_p(cm)	W_p(cm)	L_{ap}(cm)	W_{ap}(cm)	L_f(cm)	fr(GHz) (HFSS)	fr(GHz) (ANN)	% Error
1	4.390	3.651	0.201	2.024	5.349	1.830	1.8	1.64
2	3.977	3.123	0.197	1.656	6.164	2.090	2.1	0.47
3	3.838	3.415	0.164	1.895	5.786	2.190	2.2	0.45
4	3.562	2.732	0.207	1.892	6.581	2.290	2.3	0.43
5	3.380	3.337	0.177	1.863	5.915	2.400	2.4	0.00
6	3.010	3.639	0.160	1.836	5.396	2.500	2.5	0.00
7	2.847	3.684	0.205	1.595	5.718	2.690	2.7	0.37
8	2.682	2.745	0.185	1.828	6.752	2.890	2.9	0.34
9	2.572	2.555	0.176	1.669	6.479	2.980	3.0	0.67
10	2.513	2.648	0.201	1.162	6.225	3.110	3.1	0.32



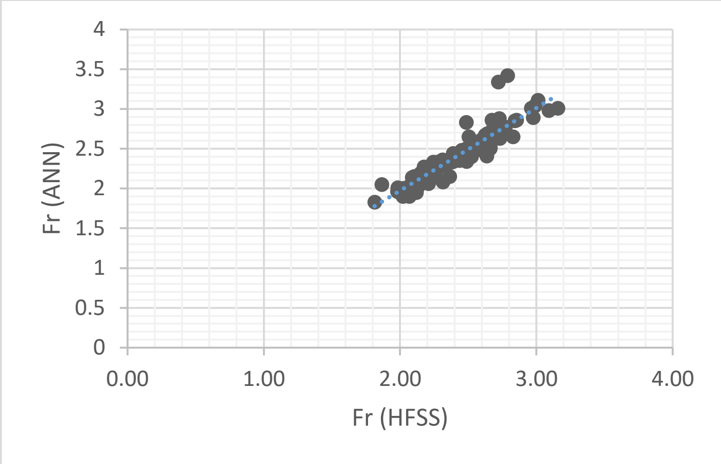


Figure 7. Test results (top) and scatter diagram (bottom) of the proposed ANN model with HFSS model.

Figure 7 also displays the correlation of the predicted frequency values and the original (HFSS) values. Correlation coefficient was measured as 0.90. Comparisons according to the running speed of the HFSS and proposed simulation model is listed in Table 3.

Table 3. Evaluation of processing time of HFSS and ANN simulation models.

	Average Time (second)	Standard Deviation
HFSS	35.82	20.44
ANN	0.0025	0.001

ANN method needed a time period of 1.32 seconds for the learning phase. In fact, the time spent for learning was even quicker than a single analysis conducted with HFSS. Test performance is rather faster than training and it was calculated as 0.025 second. Note that 0.025 second is for 100 samples. For one sample this duration will be reduced to 0.0025 second. On the other hand as Table 3 indicates, HFSS average processing time for the single ACMA design was determined as 35.82 second with a standard deviation value of 20.44. As a result, we can conclude that ANN based prediction model can be considered as much more efficient in terms of time cost and approximately ten thousand times faster than HFSS simulator software with the expense of 3.58 % generalization error. Another significant concern is that HFSS processing time exhibits relatively wide deviation although ANN has quite smaller standard deviation value, indicates proposed ANN model is more appropriate for extensive search for the prediction of resonant frequency.

CONCLUSION

ANN output frequency values were compared to the frequency values obtained from HFSS simulation. The above-mentioned characteristics of the ACMA designed with the ANN model were found to be within the acceptable margin of error (3.58%). However, the generalization error of 3.58% should be considered and optimized in the next studies.

Trained net had a quicker response time than the simulator software HFSS (for each operation, ANN was ten thousand times more fast than HFSS in average) in calculation of the required frequency values for any geometrical ACMA design. Since the response time of the proposed ANN model was shorter and faster than the numerical model, and since it provided output responses within the desired precision level for the trained neural net patterns, ANN model for ACMA designs can be considered as a preliminary search assistant for the HFSS software and can provide fast intuition about ACMA performance. Generalization accuracy performance and robustness of the ANN model could be increased by better regulating the hidden layers of the net and the ideal number of neurons it contains. The ANN model developed in this study is used only for determination of the resonance frequency, only one of the antenna parameters. On the other hand, in the future it is considered to conduct a study that would include other antenna parameters such as bandwidth, gain, routing, radiation pattern, return loss, etc. Furthermore, resonance frequency and return loss values that are known in ACMA output could be utilized as input parameters in ANN model to determine the geometric dimensions of the antenna for the output which can be called as synthesis process going to be investigated in next study.

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