Determination of Resonant Frequencies of Triangular and Rectangular Microstrip Antennas, Using Artificial Neural Networks

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Abstract

This paper presents models that can be used in the design of microstrip antennas for mobile communications. The antennas can be triangular or rectangular. The presented models are compared with deterministic and empirical models based on artificial neural networks (ANN) presented in the literature. The models are based on Perceptron Multilayer (PML) and Radial Basis Function (RBF) ANN. RBF based models presented the best results. Also, the models can be embedded in CAD systems, in order to design microstrip antennas for mobile communications.

1. Introduction

The most important applications of computational intelligence systems appeared from around 1980 and subsequent years in several areas of the human knowledge. These systems were based on Artificial Neural Networks (ANN), fuzzy modeling and Genetic Algorithms (GA). The expression Computational Intelligence (CI) was created to distinguish this class of models from those created from the traditional Artificial with Intelligence (AI), which represents and reproduce the knowledge by means of a set of rules that are automatically processed. Computational intelligence methodologies have characteristics like: learning (ANN), approximate human reasoning (Fuzzy Logic) and intelligent search (GA). In the area of microstrip antennas for mobile systems the applications arose from around 1990, according to references [1] and [2].

The resonance frequency of rectangular and triangular antennas for mobile communications must be determined with high precision because they operate in a very narrow bandwith. So, within a fabrication process of such kind of antennas, ANN based models trained with experimental data of the same class, previously collected, can preliminary estimate the resonance frequency, reducing the number of real prototypes to be constructed, saving time and resources.

In an ANN model no formula is necessary to estimate the resonance frequency of the antenna, due to its empirical nature, based on the observation of a physical phenomenon.

According to reference [1] the parameters used to estimate the resonance frequency of a rectangular antenna are: W - width, L - length h - height and e, permittivity of the substrate. According to reference [2], the parameters used to estimate resonance frequency of a triangular antenna are: a - lateral length, h - height, e permittivity of the substrate, m and n, modes of the TMmn wave.

The models can be used in a reasonable range of widths, heights, and substract permittivities, and are very adaptable to CAD systems. The mathematical formulation used in determinist methods involves extensive numeric computation and are subject to errors, like truncation errors, for example. Beyond this, this kind of analysis also requires experimental adjustments in relation to theoretical results preliminarly obtained, are time consuming, and are not adaptable to CAD systems.

2. Methodology and Mathematic Foundations

The resonance frequency of microstrip antennas is a phenomenon driven by laws whose behavior can be determined from previously known input/output samples. Empirical models like ANN, permit to estimate the resonance frequency for similar cases by interpolation, within the range where the samples were obtained.

Feedforward Perceptrons Multilayer (PML) and Radial Base Functions (RBF) models were developed, using experimental data presented in references [1] and [2], and compared with the deterministic results presented in [3] through [6] and the empirical results presented in [1] and [2].

In general, PML networks are valid alternatives, but their training is done using the backpropagation algorithm, which can present typical difficulties of the optimization algorithms based on gradient descendent methods. The major difficulties are velocity of convergence and susceptibility to local minima, increasing the computational effort and decreasing the interpretability/transparency of the results [8]. Good alternatives to the PML networks are the RBF ones.

Many different algorithms can be used with the feedforward architecture. A classical algorithm used for the training of PML neural networks is the gradient conjugate, a heuristic method. The Newton analythical method is an alternative to the gradient conjugate method, for a rapid convergence. The basic equation for the Newton method is

$$x_{k+1} = x_k - H_K^{-1} g_k \tag{1}$$

where H is a Hessian matrix (second partial derivatives) of the performance index at the current values of the weights and biases. Newton's method often converges faster than conjugate gradient methods. Unfortunately, it is complicated and expensive to compute the Hessian matrix for feedforward neural networks. There is a class of algorithms that is based on Newton's method, but it doesn't require calculation of second derivatives. These are called quasi-Newton (or secant) methods. They update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient. The quasi-Newton method that has been most successful in published studies is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update, described in reference [9], whose basic equation is:

$$?x = [J^T(x) \cdot J(x)]^{-1} J^T(x) \cdot e(x) \tag{2}$$

where J(x) is Jacobian matrix and e(x) represents the errors. BFGS algorithm was used for rectangular antennas.

For triangular antennas, the algorithm that presented best results was the Rprop - Resilient Propagation, described in reference [10]. In the Rprop algorithm the weights and learning rates are modified only once in each training epoch. Each weight w_{ji} has its own variation rate ($\triangle_{ji}$), which depends of the time t, in the following way:

$$\triangle_{ji}(t) = \begin{cases} \eta^+ \triangle_{ji}(t-1), & se \dfrac{\partial E}{\partial w_{ji}}(t-1) \cdot \dfrac{\partial E}{\partial w_{ji}} > 0 \\ \eta^- \triangle_{ji}(t-1), & se \dfrac{\partial E}{\partial w_{ji}}(t-1) \cdot \dfrac{\partial E}{\partial w_{ji}} < 0 \\ \triangle_{ji}(t-1), & \text{otherwise} \end{cases} \tag{3}$$

where$0 < \eta^- < 1 < \eta^+$.

Changes on the weights occur only when the sign of the partial derivatives with respect to the weights change, and are independent of their magnitudes.

For triangular antennas, PML networks with Rprop algorithm was more efficient than those based on conjugate gradient method [11] or those based on second order gradient, like Levemberg-Marquardt [12].

However, in the applications of this paper, RBF models presented the best results for both, rectangular and triangular antennas. The basic equation for the RBF network is:

$$\hat{y}(n+1) = \sum_{k=0}^{i} w_k(n) * \varphi(\|u(n) - z_k\|) \tag{4}$$

where $\varphi(\|u(n) - z_k\|)$ is a scalar function radially symmetric with z_k as its center. The operator $\|\cdot\|$ is the euclidian norm and gives the modulus of the argument vector. Further details about the training of this kind of network can be found in references [12] and [15].

3. Simulations

Firstly, a PML ANN with backpropagation and BFGS algorithms was used to adjust the model for rectangular antennas. The training of the network was done with regularization methods. The values for W, L, h and ε, are the inputs of the network, and the resonance frequency (f_{mn}) is the output. The best results were obtained using 2 hidden layers with 25 and 51 neurons. After this, an ANN based on RBF algorithm was used to the same input data. Table I presents the results and demonstrates the superiority of the models using RBF neural networks.

Table 1: Comparison between empirical and deterministics models C rectangular antennas.

	Resonance Frequency				
Method	Sugested RBF	Sugested PML	f_{mn} [1]	f_{mn} [3]	f_{mn} [4]
Sum of the square errors	10^{-8}	598	749	31.436	108.707
Epochs	75	3.741	200.000	-	-
Time of training	1 min.	3 hours	-	-	-

For triangular antennas the best results were obtained using an ANN with two hidden layer with 50 and 101 neurons. The better algorithm for this type of antenna was the "Resilient propagation", Rprop. Table 2 shows the results and compares them with those presented in the literature. Once more, the superiority of the RBF models is demonstrated.

Table 2: Comparison between empirical and deterministics models C triangular antennas

	Resonance Frequency				
Method	Sugested RBF	Sugested PML	f_{mn} [2]	f_{mn} [5]	f_{mn} [6]
Sum of the square errors	10^{-8}	20,3	23	326	424
Epochs	75	105.000	25.000	-	-
Time of training	1 min.	30 min	-	-	-

4. Conclusion

The results obtained using the models presented in this paper are very close to the experimental values presented in the literature. RBF based networks presented very good results, with a short time of processing. The models can be embeded in CAD systems for the design of microstrip antennas.

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