ISSN Print: 2394-7500
ISSN Online: 2394-5869
Impact Factor: 8.4
IJAR 2021; 7(4): 461-463
www.allresearchjournal.com
Received: 10-02-2021
Accepted: 19-03-2021

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Study of artificial neural networks for broadband antenna based on a parametric frequency model

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Abstract
In this paper neural network (ANN) is proposed to predict the input impedance of a broadband antenna as a function of its geometric parameters. The input resistance of the antenna is first parameterized by a Gaussian model, and the ANN is constructed to approximate the nonlinear relationship between the antenna geometry and the model parameters. A hybrid gradient descent and particle swarm optimization method is used to train the neural network. The antenna structure is then optimized for broadband operation via a genetic algorithm that uses input impedance estimates provided by the trained ANN in place of brute-force electromagnetic computations. It is found that the required number of electromagnetic computations in training the ANN is ten times lower than that needed during the antenna optimization process.

Keywords: Broadband antenna, artificial neural network, Gaussian model

Introduction

Microstrip antennas (MSAs) are used in a broad range of applications from communication systems to biomedical systems, primarily due to their simplicity, conformability, low manufacturing cost, light weight, low profile, reproducibility, reliability, and ease in fabrication and integration with solid-state devices. The design of broadband antennas is a computationally intensive task, especially when a frequency-domain electromagnetic (EM) simulator is used. Moreover, when an optimization method such as a genetic algorithm [1] is used in the design process, the antenna characteristics must be computed for thousands of hypothetical antennas over a broadband of frequencies in order to evaluate the relative merit of each configuration. In order to substitute the computationally intensive EM simulation, artificial neural networks (ANNs) [2-3] have been suggested as attractive alternatives [7]. An ANN can be suitable for modeling high- dimensional and highly nonlinear problems. When properly trained with reliable learning data, a neuromodel is computationally more efficient than an exact EM simulator, and more accurate than a model based on approximate physics.

Thus, the neural network approach has been explored in the design of microwave components and circuits such as microstrip lines [5], spiral inductors, HEMT, filters, and mixers [6]. In the antenna community, ANN has been applied to beam forming and direction-finding for arrays, as well as to microstrip antenna design. However, the use of ANN for very broadband antennas with multiple resonances has not been extensively researched yet.

In this paper, we use a neural network for predicting the input impedance of a broadband antenna via a parametric frequency model. The input resistance of the antenna is first parameterized by a Gaussian model. The Gaussian parameters are then estimated for the different training antennas, and a neural network is trained to describe the relationship between the antenna geometry and the Gaussian parameters, as shown in Fig. 1. By introducing the parametric model, the resulting ANN operates in a much less complex solution space. This leads to a smaller network size, faster training time, and more robust convergence of the training process. For the training method, a hybrid scheme combining the gradient descent method and a particle swarm optimization is utilized. Once the network for the input resistance is in place, the input reactance is generated by the Hilbert transform. This proposed technique is valid when the band of interest is broad and the resonant frequencies of the antenna are distinct. The resulting neural model is next exploited for antenna optimization. In this paper, we use the loop-based broadband antenna structure reported in as an example.

The antenna has seven geometric parameters: the lengths and heights of its three rectangular tuning arms and the radius of the antenna wire. The antenna structure is optimized for broadband operation via a genetic algorithm (GA) that uses the input impedance predicted by the ANN over a broad frequency range and over the range of antenna geometries being considered by the GA. The performance of the ANN in terms of accuracy and computational savings is evaluated in this application against a brute- force electromagnetic computation.

Gaussian-based frequency model for input resistance

The input impedance of a broadband antenna usually contains multiple resonances within the band of interest. A direct approximation of this characteristic by a neural network may lead to a large number of hidden units and is prone to failure. Furthermore, the drastic change in reactance at the resonant frequency can be difficult for the ANN to learn. In order to simplify the problem, we embed a suitable physical principle into the network so as to constrain the solution space.

We choose to model the resistance by a sum of Gaussians. The Gaussian model is simple and relatively insensitive to parameter errors. Furthermore, modeling only the resistance behavior leads to a reduced network size, improved training time, and better chance of successful training. Once the broadband resistance is modeled, the reactance can be recovered via the Hilbert transform. A Gaussian model to approximate the frequency dependent resistance envelope of a symmetric resonator can be represented as

$$\mathrm{Re}(Z(f)) = \left(\sum_k C_k . e^{\left(\frac{(f-b_k)^2}{a_k} \right)} \right) + d. \qquad \text{(i)}$$

Here, Z(f) is the impedance function; and are coefficients of the model; and is a bias.

Artificial neural net structure

An artificial neural network is next constructed to model the complex relationship between the antenna geometry and the Gaussian model parameters. For modeling the antenna geometry, the multilayered perceptron (MLP) is utilized. The MLP is a known universal approximator and has been extensively used in microwave applications. The suggested network system is illustrated in Fig. 1.

A broadband antenna for automobiles, reported earlier in, is considered as an example. It is a loop structure with three tuning arms as presented in Fig. 2.

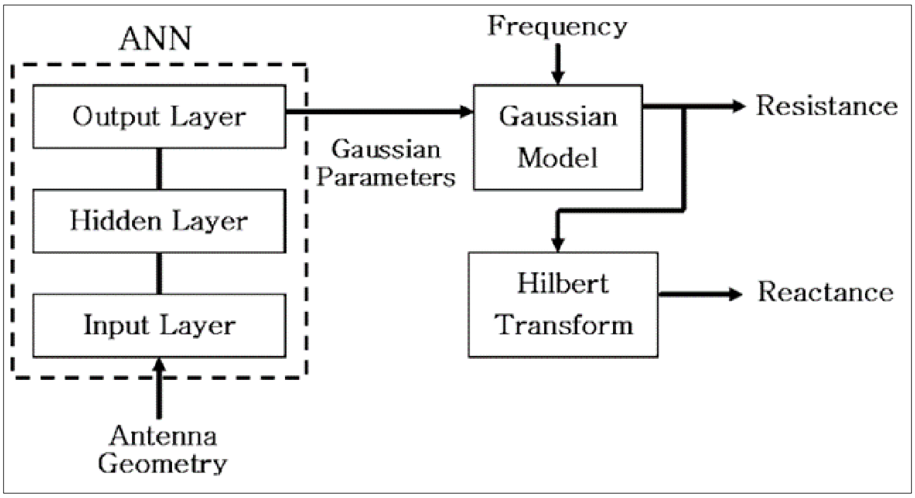

Fig 1: Impedance prediction network

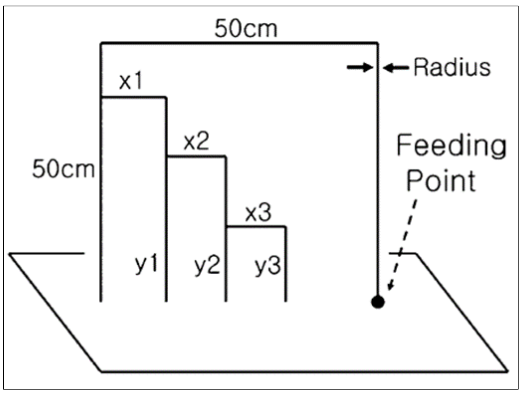

Fig 2: Antenna shape and parameters.

Broadband antenna optimization using ANN

The performance of the trained ANN is evaluated through an antenna optimization process. A GA is used to optimize the considered broadband antenna structure. In the process of the GA, the antenna impedances are generated by the trained ANN rather than by an EM simulator, as depicted in Fig. 3. The resistance is calculated using the trained neural network, and the reactance is derived from the Hilbert transform. The three lengths and three widths of the tuning arms and the wire radius are optimized within a 50 by 50 cm area. The cost function of the GA is defined as the average voltage standing-wave ratio (VSWR) in the frequency range from 170 to 220 and from 470 to 650 MHz to cover UHF analog television and digital video broadcasting.

The ANN result agrees fairly well with the NEC calculation. Their corresponding VSWR curves are plotted in Fig. 2. The dashed curve is the “GA with ANN” result and the solid curve is the true VSWR of the optimized design as calculated by NEC. The averaged VSWR as computed by NEC is 1.63 in the band of interest (the unshaded regions in the plot).

In order to gauge the performance of the developed ANN, the considered antenna is optimized again by the GA, this time using brute-force calculations by NEC for all the cost function evaluations. The GA converges after 29 iterations.

The best cost in the optimization process is 1.64. Due to the difference in the exact NEC calculation and the ANN prediction, the GA this time converges to a slightly higher optimized cost and a different optimized antenna configuration. In Fig. 4, we plot the VSWR of this optimized antenna configuration as the dotted curve. We observe that the performance of the "GA with NEC" antenna is comparable to that of the "GA with ANN" antenna.

Note that during the GA optimization using the brute-force approach, the NEC simulation must be carried out for all 2900 different antenna geometries. Using the developed neural network, however, NEC is employed only 270 times for the generation of the training and validation data sets.

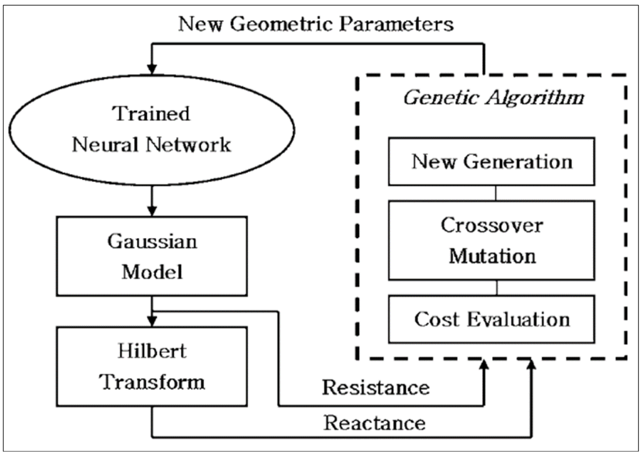

Fig 3: Genetic algorithm with the ANN

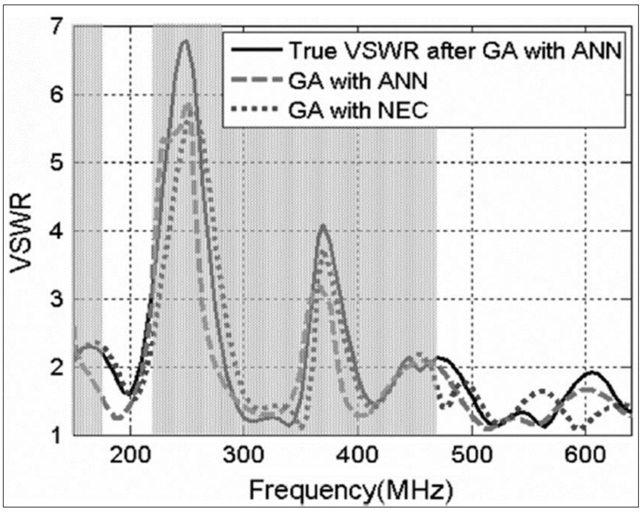

Fig 4: VSWR of the optimized antenna

Conclusion

An ANN-based system has been proposed to predict the input impedance of a broadband antenna. The input resistance of the antenna was first parameterized by a Gaussian model over a broad band of frequencies and the ANN was then constructed to approximate the nonlinear relationship between the antenna geometry and the model parameters. Introducing the model simplified the construction and training of the ANN, resulting in robust performance. The neural network was trained by using particle swarm optimization as a local search procedure seeded with an initial guess from the gradient descent learning. The reactance of the antenna was then constructed by the Hilbert transform. To test the performance of the resulting ANN, a loop antenna with multiple tuning arms was optimized by a GA, whereby the developed ANN system was used for the cost function evaluations. The performance of the ANN was compared with that of a direct approach, in which the cost function evaluation was done using the EM simulator. This indicates that a parametric frequency model used in conjunction with an ANN forms an effective framework for the design and evaluation of very broadband antennas. While the Gaussian model is found to perform adequately, other frequency models such as the rational function model may lead to even better performance.

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