Application of ANNs in Evaluation of Microwave Pyramidal Absorber Performance

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Abstract **─** To evaluate the overall anechoic chamber performance it is necessary to determine reflectivity of the absorbers. As manufacturer specifications usually give only information about frequency dependent reflection coefficient at normal incidence of EM waves, a time-consuming electromagnetic analysis is necessary to calculate the reflection coefficient at off-normal incident angles. In this paper, an efficient alternative approach to obtain the reflection coefficient at off-normal incidence is proposed. It is based on artificial neural networks trained to model the absorber reflectivity dependence on the frequency and incident angle of horizontally and vertically polarized electromagnetic waves. The model has been developed for pyramidal absorbers at low microwave frequencies (0.4 GHz–1 GHz).

Index Terms **─** Artificial neural networks, incident angle, microwave pyramidal absorber, reflectivity.

I. INTRODUCTION

The internal appearance of a radio frequency (RF) anechoic chamber, where measurements of antenna radiation patterns, electromagnetic compatibility (EMC) and radar cross section (RCS) are performed, is covered with a radiation absorber material (RAM). In an anechoic chamber, the transmitter is located at one end of the chamber and the receiver is located at the opposite end, called quite zone or test region. Generally, electromagnetic waves in the chamber propagate in all directions. Reflections from the walls, floor and ceiling affect the complex wave front at the receiver. The total electromagnetic field in this region is equal to the sum of the direct and reflected EM waves between the source of EM energy and the device under test. The RAM is specifically designed and shaped to absorb the incident RF radiation in the test region to avoid measurement errors. Various parameters that affect performance of a microwave absorber include shape, volume, dimensions, and material properties. Research in the field of radiation absorber material has been mostly focused on the development of absorbers with good performance in term of reflection at normal incidence of EM waves, reduced scattering in broad range of incident angles, greater bandwidth and reduced thickness [1-4]. The final objectives of such research have been to provide cost savings in the process of the construction of an anechoic chamber, and to improve its overall performance.

In the manufacturer specifications of a microwave pyramidal absorber, the most commonly used type of microwave absorbers, information about frequency dependent reflection coefficient at normal incidence of EM waves can be found. Absorber characteristics when incident angles deviate from normal are usually unknown. In practice, microwave absorber should offer favorable properties at off-normal incidence as well. Since these data are not available due to practical limitations of the test fixtures to measure the RF absorber reflectivity, simulations employing EM solvers are successfully used to determine the absorber performance [1-2]. A potential disadvantage of EM simulations is that they are computationally intensive for large structures such as a microwave pyramidal absorber used at frequencies below 1 GHz. Besides EM

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models, a number of numerical models are developed to optimize absorber dimensions and material parameters [3, 5-11].

In this work, we suggest an application of artificial neural networks (ANNs) in the evaluation of microwave pyramidal absorber performance. ANNs are very convenient as a modeling tool since they have the ability to learn from the presented data, and therefore, they are especially useful for problems not fully mathematically described. In other words, ANNs are able to map dependence between two datasets. The learning process is an optimization procedure through which parameters of the ANN are optimized in order to have the ANN outputs as close as possible to the desired target values. Compared to standard data fitting/interpolation technique, e.g. polynomial interpolation, ANNs have greater capability of fitting a nonlinear and complex dependency, especially in the cases where increasing the order of the used polynomials does not change fitting accuracy. Owing to the mentioned advantages ANNs have been efficiently applied in a wide range of modeling problems. There are many publications reporting the results of applications of the neural networks in the microwave area, referring to both passive and active microwave devices and circuits [13-21]. The idea presented in this paper is to replace cumbersome EM calculations requested for determining the reflectivity by an efficient neural model, i.e. to train an ANN to model reflectivity of an absorber against polarization, frequency, and incident angle. As it is shown in the paper, the developed ANN models are able to give accurate results providing significant time savings. The paper is organized as follows. In Sections II and III, the theoretical background on microwave absorbers as well as on artificial neural networks is given. The proposed approach is described in Section IV, followed by the numerical results given in Section V. The last section contains the concluding remarks.

II. MICROWAVE PYRAMIDAL ABSORBERS

Depending on the electromagnetic absorbing mechanism, dielectric and magnetic absorbers are commonly used for lining the internal appearance of the anechoic chamber. Hybrid absorbers, that combine both the magnetic and dielectric absorbers, can also be found in some anechoic chambers.

Dielectric absorbers are usually made of carbon impregnated polyurethane foam. Generally, the primary loss mechanism is the conversion of RF energy into heat, although most radiation absorber materials do not get very warm when they are illuminated by EM waves [4]. Performance of dielectric absorbers is a function of frequency-dependent electrical characteristics of the material such as relative permittivity (ε_r) and loss tangent (tan δ). In reality, losses in the dielectric are directly determined by the concentration of carbon particles in the material. Microwave absorbers using dielectric losses are electrically conductive in most cases. Dielectric absorbers are usually shaped into pyramids and wedges [1-11]. A number of such elements are fastened to the square base made of the same absorbing material. Elements are typically bounded to the metallic surfaces of the internal chamber walls, mostly by the adhesive glue of low relative dielectric constant.

The cross-section of a pyramidal absorber linearly increases towards the chamber wall having a function of impedance transformer. The propagation of an EM wave with normal incidence to the wall can be modeled as propagation across an equivalent transmission line of characteristic impedance of 377 Ω (free-space impedance). In order to achieve the optimal matching condition, the transmission line is loaded with the same impedance (metal wall covered by the absorber).

The reflectivity behavior versus frequency depends on the height of a particular pyramid, with larger pieces giving better absorption performance at lower frequencies. Consequently, the selection of pyramidal absorber for lining the internal appearance of the anechoic chamber varies depending on the lowest operating frequency. For specific applications like EMC measurements, or applications with weight restrictions, pyramidal absorbers employing high pyramids are required [6-7]. Generally, a pyramidal absorber has good performance in attenuating the reflections of electromagnetic waves when the height of pyramids is greater than the wavelength of EM waves. When an EM wave illuminates the absorber surface, it can be reflected, scattered at pyramid tips, or absorbed. At the lower frequencies, when the pyramids height becomes smaller compared to the wavelength of EM waves, performance of the pyramidal absorber rapidly deteriorates. Since the absorber dissipates only a part of the incident EM wave energy, reflections from metal walls are significantly higher than the absorption and scattering at pyramid tips.

If the geometry of an anechoic chamber is designed in such a way that the EM wave from the transmitter reaches the receiver after several reflections from the walls, floor and ceiling, the EM wave is attenuated enough, and does not affect the measurement accuracy.

To determine the reflection coefficient of a microwave pyramidal absorber sample using a 3D EM solver, in the first step, the radar cross section (RCS) of reference metallic reflector must be calculated. The RCS is a far field parameter that determines the scattering properties of a specific target. It represents a complex parameter depending on the incident wave, i.e. depending on the polarization, propagation angle, operation frequency of the incident wave and the target itself (geometry, material characteristics). A perfect electric rectangular conductor has theoretical RCS value that can be expressed as a function of the operating frequency as follows

$$\sigma = \frac{4\pi L^2 W^2}{\lambda^2}, \qquad (1)$$

where σ is radar cross section (m²), L is the length of metal reflector (m), W is the width of metal reflector (m), λ is the wavelength of the electromagnetic wave (m). Normalized value in dB can be written as

$$RCS = 10\log\left(\frac{\sigma}{\lambda^2}\right), \qquad (2)$$

and represents a reference value when the reflection of the pyramidal absorber is determined. After the RCS of a metallic reflector is obtained, a microwave absorber in the form of an array of pyramids is placed on the metal surface. RCS of the structure is then calculated. The reflection coefficient of the pyramidal absorber is determined as the difference between the RCS values of metallic reference and pyramidal absorber sample. In the case of normal incidence of the EM wave on the absorber surface, the RCS is calculated in the same direction, normal to the plane in which the metallic reflector is placed. However, if the incident angle of EM wave is off-normal (e.g. θ), the RCS is taken from the direction –θ [2].

III. ARTIFICIAL NEURAL NETWORKS

For the purpose of developing a neural model of a microwave pyramidal absorber standard multilayer ANNs can be exploited. A multilayer perceptron (MLP) neural network is shown in Fig. 1 [13]. An MLP ANN is built up of a number of elementary processing units, called neurons, which is organized into layers (an input layer, an output layer as well as several hidden layers). Every neuron in each layer is connected to all neurons from the adjacent layer but no connections are permitted between the neurons belonging to the same layer. Each neuron is characterized by an activation function and its bias, and each connection between two neurons by a weight factor.

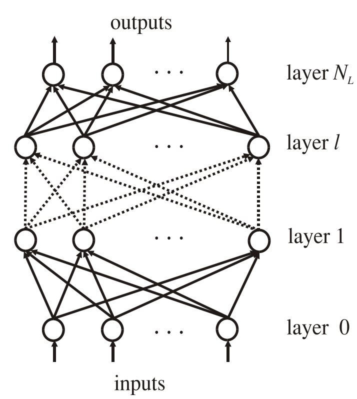


Fig. 1. Multilayer perceptron neural network.

Input signals propagate gradually from the input layer through the hidden layers up to the output layer. The output of the l-th layer can be written as

$$Y_l = F(W_L Y_{l-1} + B_l), \qquad (3)$$

where Y_l and Y_{l-1} are outputs of l-th and (l-1)-th layer, respectively, W_l is a weight matrix between (l-1)-th and l-th layer and B_l is a bias matrix between (l-1)-th and l-th layer. Function F is the activation function of each neuron and, it is linear for input and output layer and sigmoid (tan-sig in the particular case) for hidden layers [13]. With one or two hidden layers, ANNs can approximate virtually any input-output mapping.

A neural network is trained to learn relationship between sets of input-output data that are characteristics of the structure under consideration. The most known training procedure is the back propagation algorithm and its modifications such as quasy-Newton or Levenberg-Marquardt algorithms [13]. The back propagation algorithm can be described shortly as follows: after the input vectors are presented to the input neurons, the output vectors are computed. These output vectors are then compared with desired values and errors are determined. Error derivatives are then calculated and summed up for each weight and bias until whole training set has been presented to the network. The error derivatives are used to update the weights and biases for neurons in the model. The training process continues until errors are lower than the prescribed values or until the maximum number of epochs (epoch - the whole training set processing) is reached. Once trained, the network provides fast response for different input vectors, even for those not included in the training set (generalization capability, which is the most important feature of ANNs).

Having in mind that the most sensitive region of the typical neuron transfer functions is in the narrow range ([-1, 1] in the case of the tan-sigmoid function), to avoid saturation of neurons the input and output data are scaled from the original range to the normalized range [-1, 1]. Therefore the ANN response is normalized and has to be de-normalized to obtain the final output values. Normalization and de-normalization are done as described in [13].

To determine accuracy of an ANN model, average test error (ATE [%]), worst-case error (WCE [%]), and correlation coefficient, *r*, between the reference and the data simulated by the ANN are calculated, [13].

The Pearson product-moment correlation coefficient *r* is defined by:

$$r = \frac{\sum\left(x_i - \overline{x_i}\right)\left(y_i - \overline{y_i}\right)}{\sqrt{\sum\left(x_i - \overline{x_i}\right)^2 \sum\left(y_i - \overline{y_i}\right)^2}}, \qquad (4)$$

where x_i represents the reference value, y_i is the ANN computed value, $\overline{x}$ is the reference sample mean, and $\overline{y}$ is the ANN sample mean. The correlation coefficient is an indicator how the modeled values match the reference ones. If a correlation coefficient is close to one that means that MLP ANN has an excellent predictive ability, whereas a coefficient close to zero indicates poor performance of the network.

Since computing of the trained ANN response can be done practically instantaneously due to performing only basic mathematical operations and calculating elementary functions, neural models are much faster than the computatively intensive and time-consuming EM models. This ability qualifies them as very suitable to be applied in the area of modeling of different EM structures, as it is shown in this paper for the case of the microwave absorbers modeling.

IV. PROPOSED MODEL

As mentioned in Section II, determination of the reflectivity of microwave pyramidal absorbers in 3D EM solvers takes a lot of time. In order to make the time needed for the reflectivity calculation shorter, here a microwave pyramidal absorber model based on ANNs is proposed.

It consists of two ANNs trained to model dependence of the absorber reflection coefficient on the frequency and incident angle of the horizontally and vertically polarized EM wave illuminating the absorber. According to this, each ANN has two neurons in the input layer corresponding to the frequency and the incident angle and only one neuron in the output layer corresponding to the reflectivity of the modeled absorber at the desired polarization, Fig. 2.

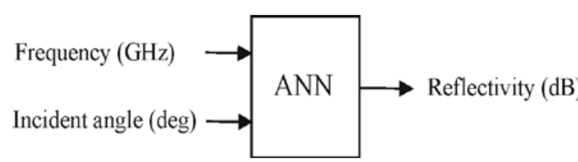


Fig. 2. Proposed ANN model.

The data used to train the ANN are values of the reflection coefficient obtained in a 3D EM solver for certain number of input combinations. Since the number of hidden neurons cannot be a priori known, it should be determined during the training process. Namely, ANNs with a different number of hidden neurons are trained and compared, and according to the test statistics, the best structure for the considered case is found. After the completed training and evaluation, the trained ANN can be used for fast calculating the reflectivity of the modeled absorber without using a 3D EM solver. It is important to note that reflectivity can be determined accurately for any input value belonging to the same range as the inputs used in the training process.

V. NUMERICAL RESULTS

The proposed model has been developed for an absorber sample of 6x6 pyramids aimed for use in an anechoic chamber at low microwave frequencies (0.4 GHz – 1 GHz).

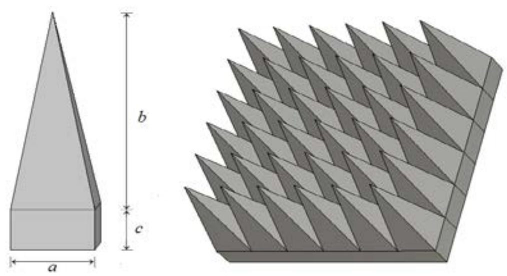
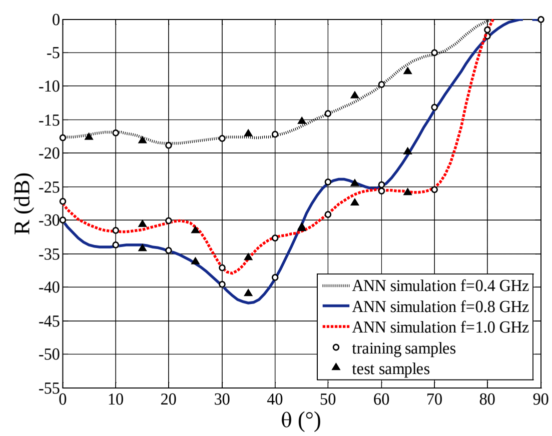


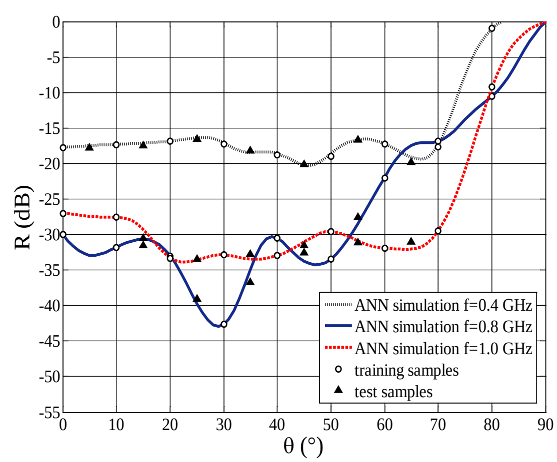
Fig. 3. Analyzed sample of the microwave pyramidal absorber (a=330 mm, b=900 mm, c=210 mm).

It is supposed that the absorber is made of carbon impregnated polyurethane foam whose complex relative permittivity is frequency dependent. At the frequency of 0.4 GHz it has a value of 1.28 – j 0.16 which gradually decreases to 1.1 - j 0.1 at 1 GHz [3]. The training and test data for ANN models are obtained using the full-wave electromagnetic solver WIPL-D [22]. ANNs for both horizontally and vertically polarized EM illuminating waves have been developed and validated independently. In both cases, the training data consisted of the training samples referring to the incidence angles from 0° to 90°, in steps of 10°. For each angle, the absorber reflection coefficient has been determined by EM simulations in the frequency range of 0.4 GHz - 1 GHz with a step of 0.1 GHz. Further, ANNs with a different number of hidden layers have been trained and tested. After intensive experimentation, it has been found that the following ANNs provided the best test statistics: for vertically polarized EM waves an ANN having two hidden layers with 15 neurons in each of them, and for horizontally polarized EM waves an ANN with two hidden layers having 20 neurons each. For the chosen ANNs, the Pearson product-moment correlation coefficient calculated for the case of the simulation of the reflectivity for the training inputs has value of 0.9999 for verically polarized EM waves, and 0.9998 for horizontally polarized EM waves.

To illustrate accuracy of the proposed model, i.e. to show how much the ANNs have learned the training data and how much are capable to generalize, in Figs. 4 and 5 there is the reflectivity plotted against the incidence angle. Figure 4 refers to the training frequencies (0.4GHz, 0.8 GHz, and 1 GHz), whereas Fig. 5 refers to the frequency not used for the training (0.85 GHz).



(a)



(b)

Fig. 4. Reflectivity performance of the microwave pyramidal absorber at training frequencies for (a) vertically and (b) horizontally polarized EM waves.

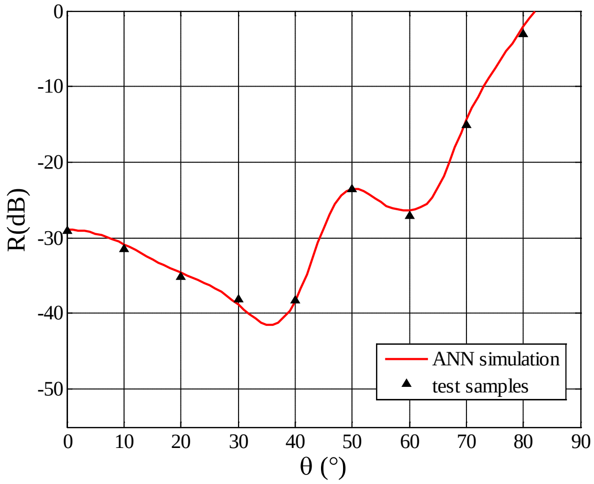


Fig. 5. Reflectivity performance of the microwave pyramidal absorber at test frequency f=0.85 GHz for vertically polarized EM waves.

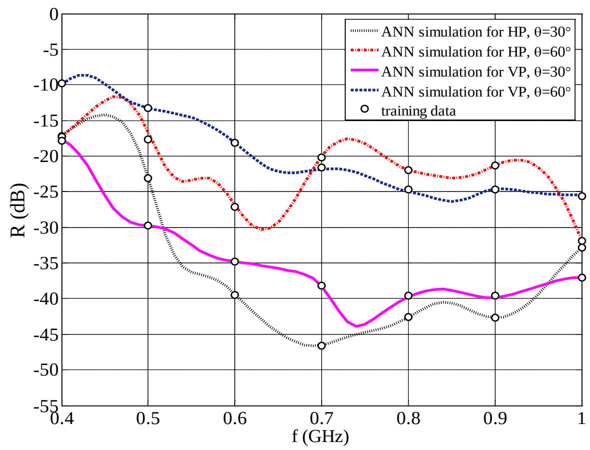


Fig. 6. Reflectivity performance of the microwave pyramidal absorber for different incident angles of EM waves.

In addition, the reflectivity versus frequency for both polarizations and different incidence angles is plotted in Fig. 6.

Lines represent the reflectivity simulated by the ANN models, whereas the symbols refer to the reference data obtained by the EM solver. Circles correspond to the training values of the incidence angles and triangles correspond to the values of the incident angle not used for the network training.

A good agreement of the simulated and the reference values for both training and test samples confirm the ability of the ANN model to simulate accurately the absorber reflectivity for different inputs. As an additional illustration, in order to compare the reflectivity simulated by the EM solver with the one obtained by the ANN model, in Fig. 7. There are reflectivity values used for the training purposes calculated by the EM solver and the reflection coefficient simulated by the ANN model in steps of 0.01 GHz for the frequency, and 1° for the incident angle. The plots confirm that the ANN model calculates the reflectivity with the same accuracy as the EM solver.

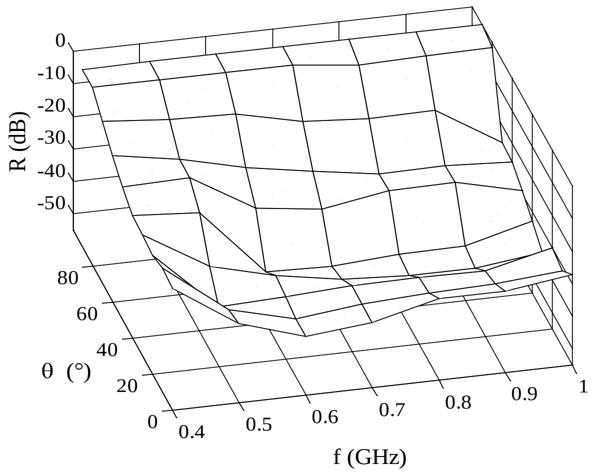
Using the ANN model instead of the EM solver significant time savings can be provided. For example, to calculate the reflectivity for one input combination (one frequency point at a fixed incident angle) in WIPL-D, the simulation time was 0.5 minutes at 0.4 GHz, and 25 minutes at 1 GHz. Simulations were performed at a Pentium dual-core computer (2 GHz CPU with 4GB RAM memory). With further increasing of the operating frequency, the EM solver needs more time to calculate reflectivity since the structure of the absorber sample becomes electrically larger. On the other side, ANN trained to predict the reflectivity of the absorber can determine the reflectivity for a given input combination in a matter of second, independently of the operating frequency.

VI. CONCLUSION

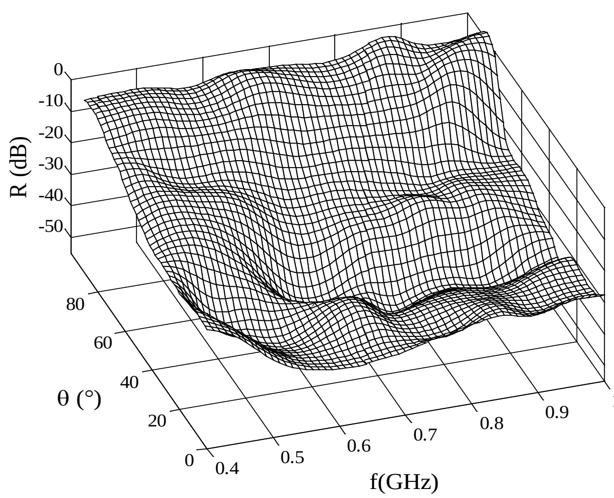
In this paper, modeling of microwave pyramidal absorber utilizing artificial neural networks (ANNs) is reported. An ANN model has been developed to estimate absorber performance at different incident angles of electromagnetic waves and operating frequencies, for vertical as well as horizontal polarization. For model development, the reflectivity calculated by the EM solver has been used. As illustrated, the reflectivity calculated by the ANN model is very close to the reference reflectivity obtained by the EM solver. Once trained ANN model calculates the reflectivity directly, outside the EM solver, not by subtracting RCSs of the metallic reflector and the pyramidal absorber sample as it is usually done in 3D EM solvers, consequently saving the simulation time while maintaining the accuracy as illustrated in the presented example.

The ANN model simulates reflectivity in a matter of seconds independently of the operating frequency, which is its advantage over the EM solvers where simulation time depends on the frequency and is order of tens of minutes.

Therefore, a new design methodology that is both accurate and fast at the same time can be an alternative solution to time-consuming simulations using full-wave electromagnetic solvers.



(a)



(b)

Fig. 7. Reflectivity performance of the microwave pyramidal absorber (a) training samples calculated by the full-wave EM solver (b) simulated by the ANN model.

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REFERENCES

[1] B. K. Chung and H. T. Chuah, "Modeling of RF Absorber for Application in the Design of Anechoic Chamber," *Progress in Electromagnetics Research (PIER)*, vol. 43, pp. 273-285, 2003.

[2] B. B. Janić and B. M. Kolundžija, "RF Absorber Reflectivity Evaluation using RSC Calculation," *IEEE AP-S International Symposium 2007*, Honolulu, Hawaii, USA, pp. 6043-6046, June 2007.

[3] A. Khajehpour and S. A. Mirtaheri "Analysis of Pyramid EM Wave Absorber by FDTD Method and Comparing with Capacitance and Homogenization Methods," *PIERS*, vol. 3, pp. 123-131, 2008.

[4] J. T. Gear, "Microwave Absorbers Manage Military Electronics RF Interference," *Defense Electronics*, pp. 6-9, 2004.

[5] H. Anzai, M. Saikawa, Y. Naito, and T. Mizumoto, "The Equivalent Representation of Pyramidal Absorbers and its Application to the Analysis of Electromagnetic Wave Absorber's Characteristics," *Proceedings of the IEEE International Symposium on EMC*, Atlanta, USA, pp. 563-567, 1995.

[6] C. L. Holloway, P. M. McKenna, R. A. Dalke, R. A. Perala, and C. L. Devor, "Time-Domain Modeling, Characterization, and Measurements of Anechoic and Semi-Anechoic Electromagnetic Test Chambers," *IEEE Trans. on EMC*, vol. 44, no. 1, pp. 102-118, 2002.

[7] E. Kuester and C. A. Holloway, "A Low-Frequency Model for Wedge or Pyramid Absorber Arrays-I: Theory," *IEEE Trans. on EMC*, vol. 36, no. 4, pp. 300-307, 1994.

[8] S. Kent and M. Kartal, "Dielectric Absorber Design for Wide Band–Wide Oblique Incidence Angle using Genetic Algorithm," *Int. J. Electron. Commun. (AEÜ*), vol. 61, pp. 398-404, 2007.

[9] E. Michielssen, J. M. Sajer, S. Ranjithan, and R. Mittra, "Design of Lightweight, Broad-Band Microwave Absorbers using Genetic Algorithms," *IEEE Trans. on MTT*, vol. 41, no. 6/7, pp. 1024-1031, 1993.

[10] S. Kent and M. Kartal, "Genetic Algorithm Approach on Pyramidal Dielectric Absorbers," *Int. J. of RF and Microwave Computer-Aided Engineering*, vol. 18, no. 3, pp. 286-294, 2008.

[11] T. Kaufmann, K. Sankaran, and C. Fumeaux, "A Review of Perfectly Matched Absorbers for the Finite-Volume Time-Domain Method," *Applied Computational Electromagnetic Society (ACES) Journal*, vol. 23 no. 3, pp. 184-192, 2008.

[12] E. A. Hashish and S. M. Eid, "Design of Wideband Planar Absorbers using Composite Materials," *Applied Computational Electromagnetic Society (ACES) Journal*, vol. 24, no. 4, pp. 413-418, 2009.

[13] Q. J. Zhang and K. C. Gupta, *Neural Networks for RF and Microwave Design*, Artech House, Inc. Norwood, MA, USA, 2000.
[14] C. Christodoulou and M. Gerogiopoulos, *Applications of Neural Networks in Electromagnetics*, Artech House, Inc. Norwood, MA, USA, 2000.
[15] S. S. Gultekin, K. Guney, and S. Sagiroglu, "Neural Networks for the Calculation of Bandwidth of Rectangular Microstrip Antennas," *Applied Computational Electromagnetic Society (ACES) Journal*, vol. 18, no. 2, pp. 110-120, 2003.
[16] J. E. Rayas-Sanchez, "EM-Based Optimization of Microwave Circuits using Artificial Neural Networks: The State-of-the-Art," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 420-435, Jan. 2004.
[17] V. Marković and Z. Marinković, "HEMT Noise Neural Model Based on Bias Conditions," *COMPEL*, Emerald, vol. 23, no. 2, pp. 426-435, 2004.
[18] L. Zhang, Q. -J. Zhang, and J. Wood, "Statistical Neuro-Space Mapping Technique for Large-Signal Modeling of Nonlinear Devices," *IEEE Trans. on MTT*, vol. 56, no. 11, pp. 2453-2467, 2008.
[19] R. Ghayoula, N. Fadlallah, A. Gharsallah, and M. Rammal, "Design, Modeling, and Synthesis of Radiation Pattern of Intelligent Antenna by Artificial Neural Networks," *Applied Computational Electromagnetic Society (ACES) Journal*, vol. 23, no. 4, pp. 336-344, 2008.
[20] H. Kabir, Y. Cao, and Q. Zhang, "Advances of Neural Network Modeling Methods for RF/Microwave Applications," *Applied Computational Electromagnetic Society (ACES) Journal*, vol. 25, no. 5, pp. 423-432, 2010.
[21] Z. Marinković, G. Crupi, A. Caddemi, and V. Marković, "Microwave FinFET Modeling Based on Artificial Neural Networks Including Lossy Silicon Substrate," *Microelectronic Engineering*, vol. 88, no. 10, pp. 3158-3163, 2011.
[22] WIPL-D Pro v7.1, "*Software and User's Manual*," WIPL-D d.o.o., Belgrade, 2009.

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