Soft Computing Techniques for Free-Space Measurements of Complex Dielectric Constant

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***Abstract* –** A novel method for estimating the dielectric properties of materials by applying different soft computing techniques is presented. Dielectric properties allow us to know other material characteristics such as moisture content, bio-content, chemical concentration, etc., which are of great importance on industrial or science fields. In this paper, we present a free-space measurement method along with soft computing techniques, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), and other approaches like Artificial Neural Networks (ANN), for estimating the dielectric properties of materials. The proposed method is validated by measurements and synthetic materials, which were generated to test the performance of these soft computing algorithms.

I. INTRODUCTION

For many years, the evaluation of dielectric properties of materials has been a fundamental aspect and a challenging problem with an important variety of applications [1]. There are several works focused in the estimation of dielectric properties of materials in the investigations of material and structural assessment [2, 3]. Application of materials in the aerospace, textile, microwave, microelectronics, and communication industries requires the exact knowledge of material parameters such as permittivity and permeability [4, 5, 6]. Complex dielectric permittivity and magnetic permeability (ϵ_r^*, μ_r^*) are two fundamental parameters that describe the response of matter to the external electric and magnetic fields. Nowadays, a heightened interest on the development of new methods that provide accurate determination of both parameters has arisen, particularly, from the fact that contemporary Electronic Design Automation (EDA) software contribute to the design process by allowing us to extensively characterize a constructed device prior to making a physical prototype. To prepare a trustworthy simulation, it is necessary to have good knowledge of the dielectric properties of all media involved.

During the last years, INTA's Detectability Lab has investigated in the field of material measurements [7, 8], as well as in characterization of their electromagnetic properties [9, 10] for radar applications (protective/coating materials, Radar Absorbing Materials (RAM),...) in which a plane wave will impinge on a target. There are many ways to measure the complex electromagnetic constants of samples in the time and frequency domain [11] and they all basically fall into two categories: either destructive methods, in which sample preparation is needed for accurate evaluation, or nondestructive methods, which require very little or no sample preparation [12]. The measured quantity(s) of the sample will enable the computation of its permittivity and permeability.

The open-ended coaxial probe is a cut-off section of a transmission line. The material is measured by immersing the probe into a liquid or touching it to the flat face of a solid (or powder) material. The method offers the advantages of being a broadband and nondestructive method, but in the case of solids requires perfect contact between the probe and the sample. The surface roughness of the sample seriously limits the accuracy of the measurement [13]. Other techniques such as the perturbation of a resonant cavity by the introduction of a dielectric sample can be utilized to compute electrical properties by measuring the change in resonant frequency and its quality factor. However, the sample should fit exactly into the sample holder, and small misalignments can cause large measurement errors [14]. Recently, the methods based on numerical techniques have been arising due to the increase of capacity and accuracy of the numerical methods [15, 16].

In the free-space method (Fig. 1), the antennas focus microwave energy at the measurement plane, and the sample is fixed at the common focal plane between the two antennas. Since the sample is at the focal plane of the antenna and is not in contact with the applicator, it can be adapted easily for measurements at high or low temperatures and hostile environments [17]. Traditionally, whatever the measurement method may be, an iterative process need to be implemented to find the roots of the error function and extract complex permittivity and permeability (ϵ, μ) from the measured quantity(s) [18].

Soft computing is a general term covering a number of methodologies, where the common thread through all of them is that, unlike conventional algorithms, they are tolerant of imprecision, uncertainty, and partial truth. Soft

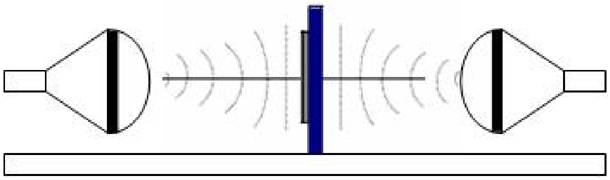

Fig. 1. Free-space measurement set-up.

computing techniques offer adaptivity, since they can track a changing problem quite well. The aim of this paper is to apply soft computing techniques to estimate the electromagnetic characteristics of materials, using the free-space method. First, the measurement method is described and the problem is defined. Then, the soft computing techniques used in our experimentation are presented. This techniques are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN). GA and PSO are used to obtain the dielectric constant from artificial, synthetic materials. After that, different topologies of ANNs are applied to the same set of materials to compare performance. Finally, these techniques are used on real measurements obtained from INTA's anechoic chamber.

II. PROBLEM DEFINITION

In this section, a theoretical representation of the estimation problem is introduced. The free-space method employed at INTA follows the configuration shown in Fig. 2(a), where a PC controls the positioner and a Vector Network Analyzer (VNA), which is also connected to a transmitting and receiving antenna. For radar applications, this method has some advantages:

1) Allows broadband and contactless nondestructive measurements.
2) The materials are measured under free-space conditions, which are the same conditions of the actual applications of the these materials.
3) The samples used must not be highly elaborated in shape.

Using this setup, S_{11} parameter is measured and reflection coefficient is obtained for a metal-backed sample (Fig. 2(b)). From transmission line theory, reflection coefficient is related to complex permittivity and permeability via the following general equations (no assumptions or approximations for low losses materials have been made) derived from [19],

$$\Gamma_{\perp} = \frac{\sqrt{\frac{\mu_r^*}{\epsilon_r^*}}cos(\theta_i)tanh(jk_0 d\sqrt{\mu_r^*\epsilon_r^*}cos(\theta_t)) - cos(\theta_t)}{\sqrt{\frac{\mu_r^*}{\epsilon_r^*}}cos(\theta_i)tanh(jk_0 d\sqrt{\mu_r^*\epsilon_r^*}cos(\theta_t)) + cos(\theta_t)} \tag{1}$$

$$\Gamma_{\parallel} = \frac{\sqrt{\frac{\mu_r^*}{\epsilon_r^*}}cos(\theta_t)tanh(jk_0 d\sqrt{\mu_r^*\epsilon_r^*}cos(\theta_t)) - cos(\theta_i)}{\sqrt{\frac{\mu_r^*}{\epsilon_r^*}}cos(\theta_t)tanh(jk_0 d\sqrt{\mu_r^*\epsilon_r^*}cos(\theta_t)) + cos(\theta_i)}, \tag{2}$$

where $\Gamma_{\perp}$ and $\Gamma_{\parallel}$ are perpendicular and parallel reflection coefficients, d is the sample thickness, $k_0 = \frac{2\pi}{\lambda}$ is the free-space wavenumber, θ_i is the incidence angle, θ_t the transmitted angle (Fig. 2(b)) and ϵ_r^* and μ_r^* are relative complex permittivity and permeability,

$$\epsilon_r^* = \epsilon_r^{'} - j\epsilon_r^{''} \tag{3}$$

$$\mu_r^* = \mu_r^{'} - j\mu_r^{''}. \tag{4}$$

Because ϵ_r^* and μ_r^* cannot be easily expressed in terms of the reflection coefficients and d, this paper propose to find them by soft computing techniques.

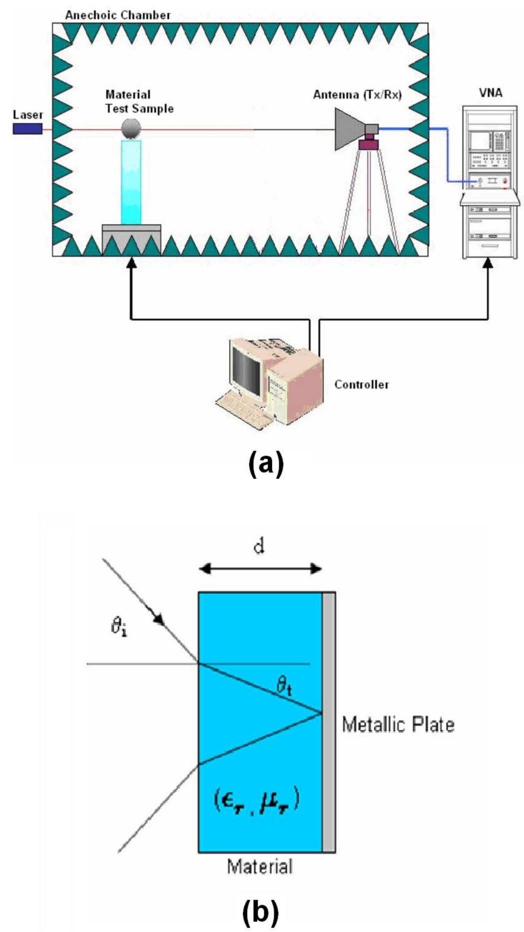

Fig. 2. Measurement set-up in anechoic chamber.

III. SOFT COMPUTING TECHNIQUES IN THE ESTIMATION OF DIELECTRIC PROPERTIES OF MATTER

Bearing in mind equations (1) and (2), the first approach to solve the problem has been the use of Genetic Algorithms (GA) and PSO algorithms, that looks for the proper values of ϵ_r^* and μ_r^* starting from the reflection coefficients of the test samples.

A. Genetic Algorithms

Evolutionary algorithms are a broad class of stochastic optimization algorithms, inspired in the biological process that allow populations to adapt to their surrounding environment [20]. One of the first proposals of these kind of algorithms was the Genetic Algorithms (GA) by John Holland [21]. GA maintains a population of candidate solutions to a specific problem, and makes it evolve by iteratively applying a set of stochastic operations, known as mutation, recombination, and selection [22]. In GA, individuals are codified as strings of binary digits, which represent the solution to the problem and it is called chromosome. The selection of the best candidate solution (or chromosome) is guided by how the candidate solution minimize a fitness function.

For the work contained in this document, MATLAB has been used to perform the optimization by GAs (*Genetic Algorithms and Direct Search Toolbox*). This implementation of GA uses several typical parameters such as population size (*PopulationSize*), number of generations (*Generations*), number of individuals to be kept for next generation (*EliteCount*), selection, crossover and mutation functions (*SelectionFcn, CrossoverFcn, MutationFcn*), etc, which can be adjusted and modified.

The main GA parameters selected in our experimentation are depicted in table 1.

B. Particle Swarm Optimization

Particle swarm optimization (PSO) is a recently proposed algorithm by James Kennedy and R. C. Eberhart in 1995 [23], motivated by social behavior of organisms such as bird flocking and fish schooling. PSO are very similar to Genetic Algorithms, where a population of random solutions is initialized and the aim is the search for optima by updating generations. However, in PSO there is no evolution operators such as crossover or mutation. The potential solutions, called particles, '*fly*' through the problem space by following the current optimum particles.

This optimization approach was first applied to electromagnetic by [24]. In this case, a PSO code has been programed specifically for this work. For the propose of our experimentation, authors have developed a PSO tool that includes a graphical user interface that permits different simulations varying easily its parameters, and seeing its results and convergence. The main parameters used to obtain the results contained in this paper are presented in table 1.

IV. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) have their origin in the attempt to simulate by mathematical means an idealized form of the elementary processing units in the brain and of their interconnections, signal processing, and self-organization capabilities [20]. An important issue about ANN is the ability to progressively improve their performance on a given task by somehow learning how to do the task better. They are at their best for problems where there is little or incomplete understanding, so that building a faithful mathematical model is difficult or even impossible.

Our next approach to solve the described problem is to model it through ANNs using the *Neural Network Toolbox* provided by MATLAB.

The actual reflection coefficients measured in the anechoic chamber are contaminated with noise and it is well known the skill of ANNs to adapt its behavior to noisy signals and to obtain good results. Moreover, before feeding the search algorithms with the actual reflection coefficients, some kind of preprocessing must be done. For the case of ANNs, this preprocessing can be avoided, reducing the time and complexity of the process.

Another theoretical advantage is the fact that the ANN training is time and computational consuming, but is done only a limited number of times, and after that the determination of the dielectric constants for a material is practically instantaneous. On the other hand, the search algorithm (GA or PSO) is time consuming each time it is executed. So, the global computational cost derived from the ANNs will be less than the derived from the GA or PSO.

V. RESULTS

For this first approach, both synthetic and real materials are used to test the algorithms proposed. As actual available materials in our lab are non-magnetic, there is no need to measure off-normal, so $\theta_i = 0$ and equations (1) and (2) are the same, and consequently one of them is enough to extract real (ϵ_r') and imaginary parts (ϵ_r'') of ϵ_r^*. For this reason, the synthetic materials created are non-magnetic and the problem is reduced to the estimation of the dielectric permittivity. This simplification diminish the complexity of the problem but does not limit its utility as the conclusions could be easily extrapolated to oblique incidence and μ_r^* determination.

A. GA and PSO

Given electric permittivity, thickness, and frequency, reflection coefficients can be calculated from equation (1). Table 2 shows the fifteen different synthetic materials generated.

For each of these materials, GA and PSO are applied separately using the MATLAB *Toolbox* and the tool developed respectively. For the GA the genes are formed by two chromosomes whereas for PSO each position vector has also two coordinates, it is, in both cases, real and imaginary parts of ϵ_r^* are searched. Codification is real for both alternatives and the chosen fitness function to be minimized is,

Table 1. GA and PSO parameters.

GA		PSO	
Parameter	Value	Parameter	Value
PopInitRange	[1 0;20 20]	Range	[1 0;20 20]
PopulationSize	50	Population	20
EliteCount	4	C1, C2	2
Generations	100	Iterations	140
SelectionFcn	@selectionroulette	Initial inertia	0.9
CrossoverFcn	@crossoverintermediate,0.5	Final inertia	0.4

Table 2. Synthetic materials.

Material	$\epsilon_r^{'}$	$\epsilon_r^{''}$	$d(mm)$	Freq. (GHz)
AR1	2	0	2	8-12.4
AR2	5	0	2	8-12.4
AR3	10	0	2	8-12.4
AR4	10	1	2	8-12.4
AR5	10	10	2	8-12.4
AR6	2	0	1	8-12.4
AR7	5	0	1	8-12.4
AR8	10	0	1	8-12.4
AR9	10	1	1	8-12.4
AR10	10	10	1	8-12.4
AR11	2.45	0	0.796	8-12.4
AR12	2.55	0	1.589	8-12.4
AR13	2.01	0	1.539	8-12.4
AR14	9.8	0	1.234	8-12.4
AR15	2.2	5.2	1.2	8-12.4

$$f = |Re(\Gamma_{\perp actual}) - Re(\Gamma_{\perp iteration})| + |Im(\Gamma_{\perp actual}) - Im(\Gamma_{\perp iteration})| . \quad (5)$$

The output of both algorithms is excellent, as they can match the desired real and imaginary parts of the complex permittivity for all the cases at all the frequencies with practically inexistent error. As an example, material AR15 is shown in Fig. 3.

To emulate the measurement error and evaluate its influence in the determination of $\epsilon_r^{'}$ and $\epsilon_r^{''}$, the reflection coefficient related to AR15 is contaminated with a gaussian error (zero mean and a variance of 0.5 dB in modulus and 0.1 in phase). The results obtained are nearly the same for GA and PSO (Fig. 4), and the influence of this error become clear, deriving in an incorrect estimation of ϵ_r^*.

In the next step, a 20x20 cm real sample of Arlon© CuClad 250GX-0620 55 11 is measured in the anechoic chamber, and the reflection coefficient is treated with GA and PSO to obtain the dielectric constant. The sample has a thickness of $d = 1.70\ mm$ and the manufacturer asserts that its nominal real part and loss tangent ($tan\delta = \frac{\epsilon_r{''}}{\epsilon_r{'}}$) are 2.55 and 0.0022 respectively, with minimum variations over a wide frequency band[1]. Comparisons with results obtained with the estimation presented in this paper are shown in Fig. 5, proving that soft computing techniques are a good and easy-to-implement alternative. This good results are supported by the fact that the actual measurement error is lower than the proposed for AR15.

[1]The measurement method followed by Arlon© is the accepted industry standard IPC TM-650 2.5.5.5, a stripline resonator test for permittivity and loss tangent (dielectric constant and dissipation factor) at X-Band–3/98

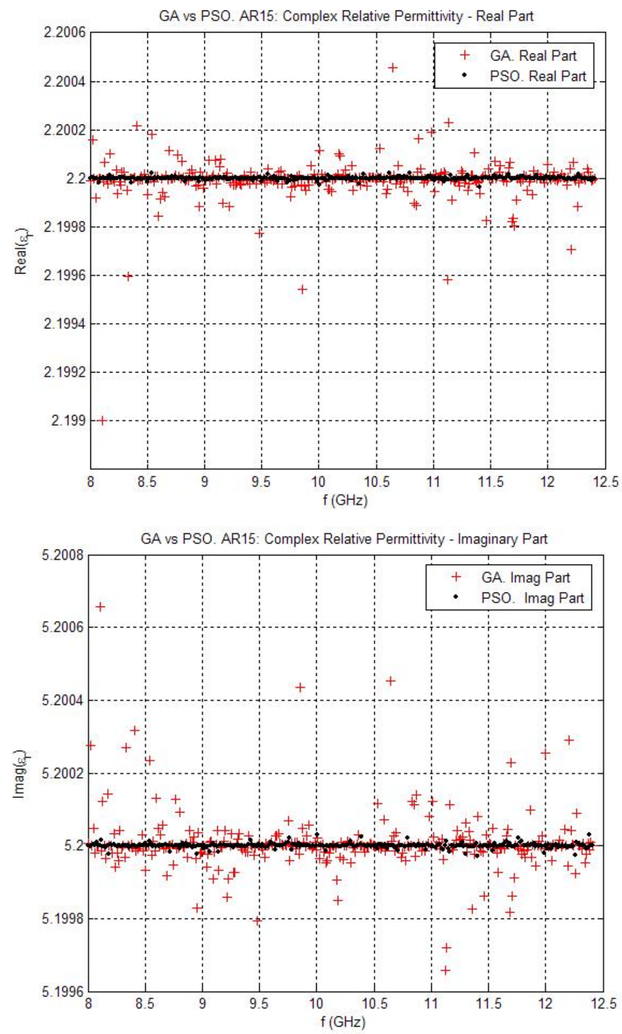

Fig. 3. Estimated real and imaginary part of AR15 for GA and PSO.

B. ANN

Different multilayer feed-forward backpropagation networks are designed. All of them have four inputs and

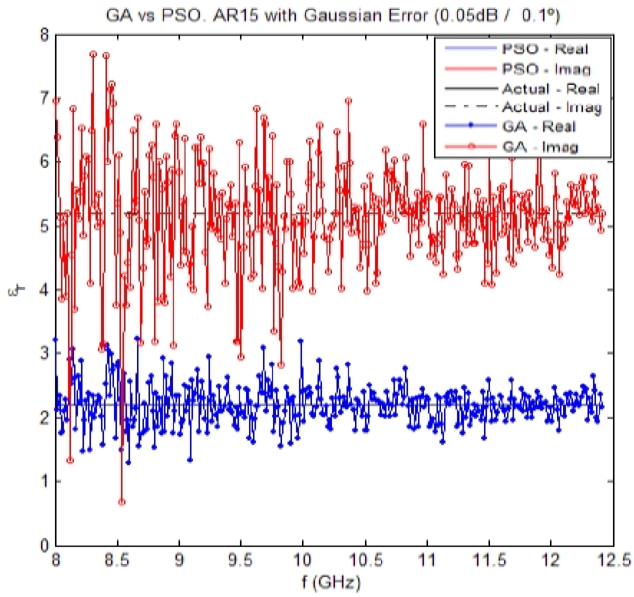

Fig. 4. GA and PSO results for AR15 reflection coefficient contaminated with noise.

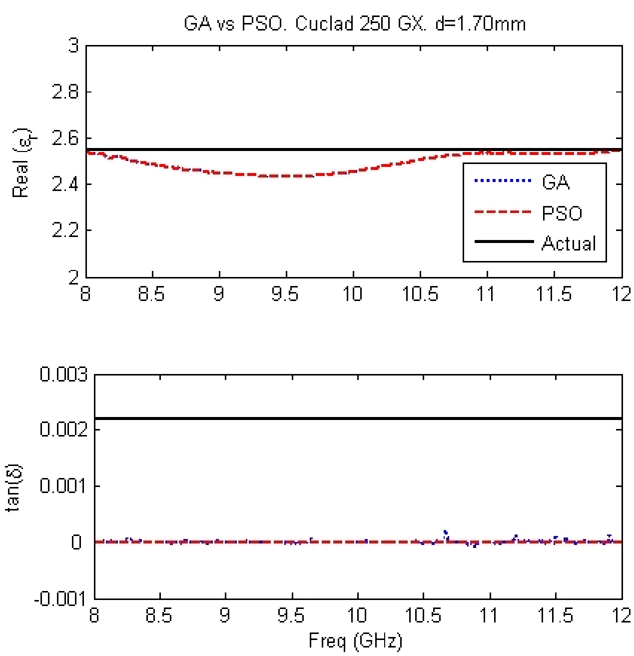

Fig. 5. Real part and loss tangent estimation with GA and PSO of CuClad 250GX.

two outputs. The inputs are the real and imaginary parts of the reflection coefficient, the frequency and the thickness of the sample and the two outputs are the real and imaginary parts of complex relative permittivity (Fig. 6). For training, validation and test, a set of twenty synthetic materials is used, where random values have been chosen: $\epsilon_r^{'} \in [1, 10]$, $\epsilon_r^{''} \in [0, 10]$ and $d \in [0.5, 2]$ mm. After grouping the materials by frequency, 1/2 of data is used for training, 1/4 for validation and 1/4 for test.

Minmax normalization is applied for input and output parameters and hyperbolic tangent sigmoid transfer function (`tansig`), linear transfer function (`purelin`) and Levenberg-Marquardt backpropagation (`trainlm`) are used as hidden layers activation function, output layer activation function and training function respectively.

Different architectures have been tested, namely with one hidden layer and 10, 15 or 20 neurons and with two hidden layers with 20-10 neurons or 25-15 neurons. Starting at a given value, increasing the number of layers and neurons, the net follows better the training, test and validation materials but fails in predicting new materials.

The best output is achieved for the one layer and 20 neurons case. In Fig. 7, it can be seen the training performance for the materials used for test in this configuration.

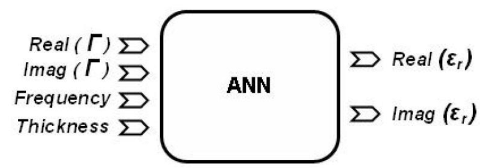

Fig. 6. Artificial neural network inputs and outputs.

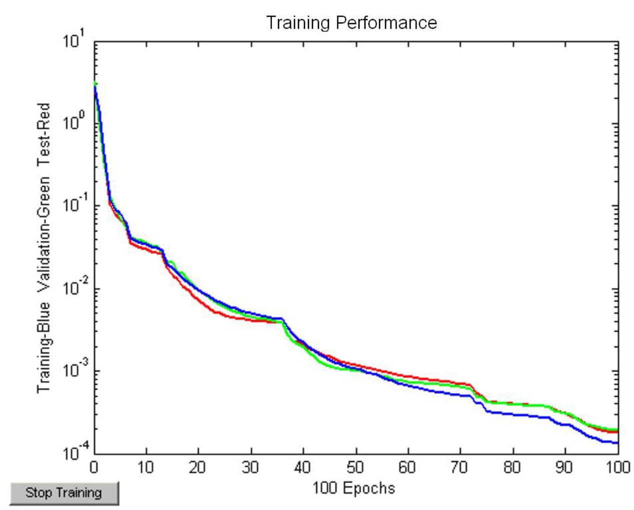

Fig. 7. Training Performance: 1 Layer and 20 neurons.

The result for AR15 material (table 2) without noise is presented in Fig. 8 and with noise in Fig. 9. Figure 9 also shows the performance for the synthetic test material ARPr (with dielectric constant $\epsilon_r^{'} = 6.52$ $\epsilon_r^{''} = 2.22$). Simulations show that GA and PSO have better performance than ANN except for the case of AR15 with noise.

The measurements made for Arlon© CuClad 250GX-0620 55 11 are introduced to the trained network and the output obtained is presented in Fig. 12. GA and PSO approaches show better performance also for the real measurement.

At this point, the net is trained with the random artificial materials but adding gaussian noise in phase

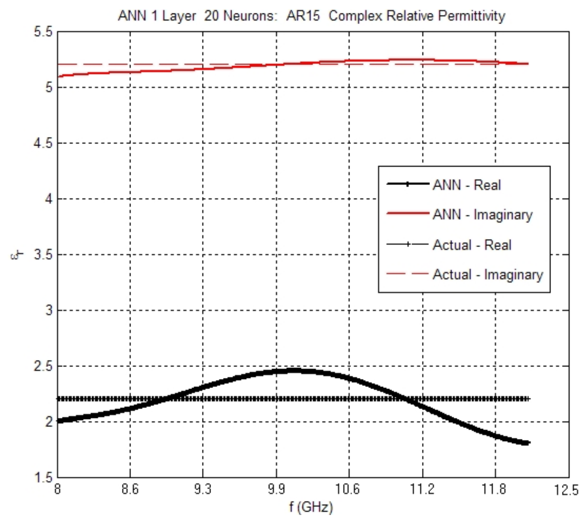

Fig. 8. ANN applied to synthetic material AR15: 1 layer, 20 neurons.

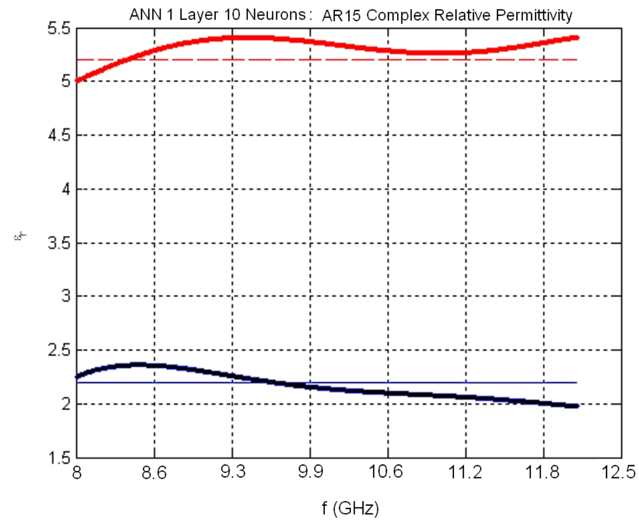

Fig. 10. ANN applied to synthetic material AR15: 1 layer, 10 Neurons.

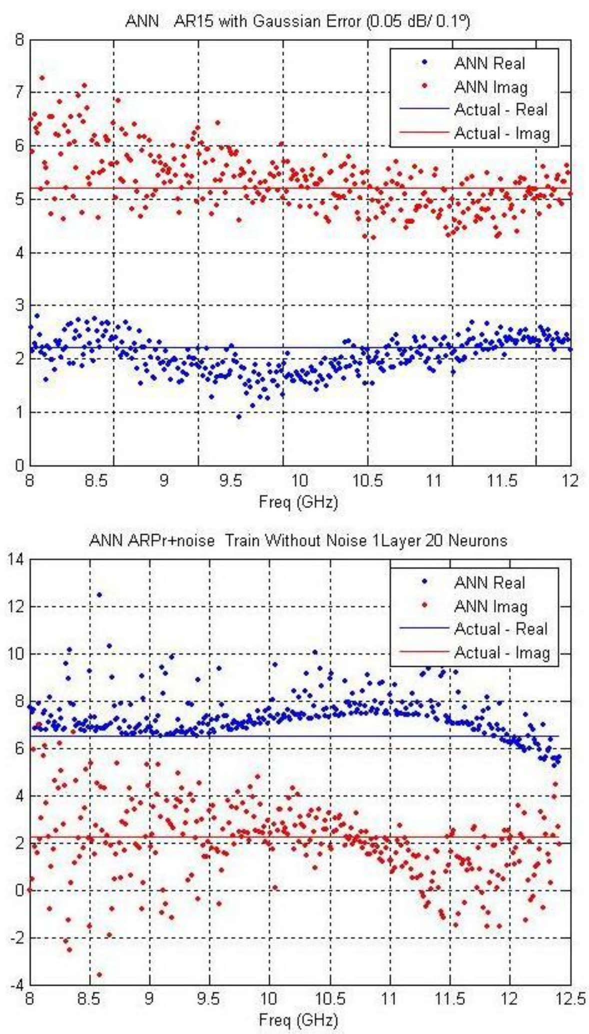

Fig. 9. ANN applied to contaminated synthetic material AR15 and ARPr: 1 layer, 20 neurons.

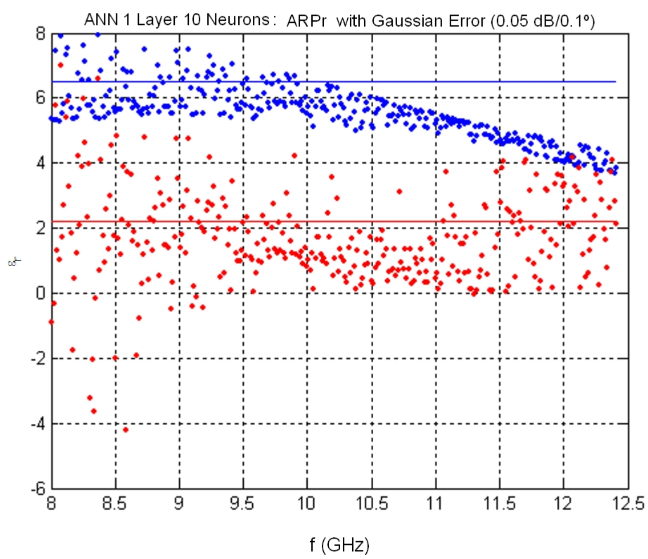

Fig. 11. ANN applied to synthetic material ARPr+Noise: 1 layer, 10 Neurons.

and amplitude (with zero mean and 0.05dB and 0.1 of variance) to the odd materials. Then, half of the training, test and validation samples contains noise. In this case, the adaptation of the net to the training materials is worse, and the training error is higher. The best output is achieved for the one layer and 10 neurons case. Figure 13, shows the training performance for the materials used for test in this configuration.

The results for AR15 and ARPr+Noise can be seen in Figs. 10 and 11. It can be appreciated that no improvement has been reached with this training.

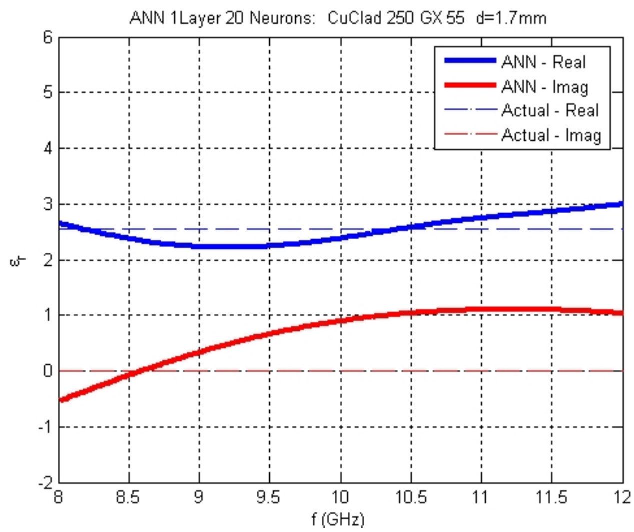

Fig. 12. ANN applied to measured Arlon© CuClad 250GX-0620 55 11: 1 layer, 20 neurons.

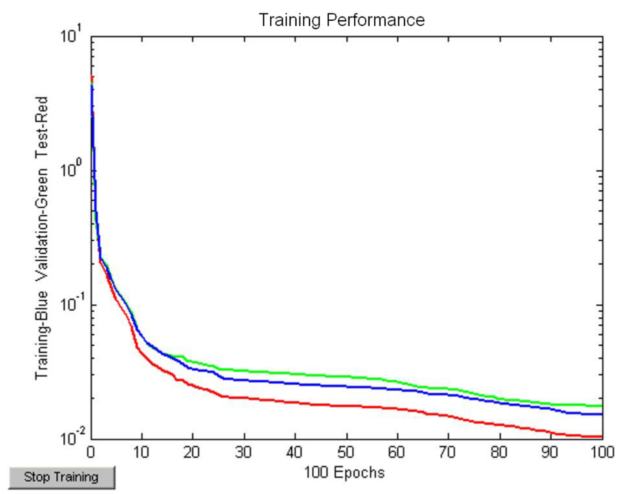

Fig. 13. Training Performance: 1 layer, 10 neurons.

VI. CONCLUSIONS AND FUTURE WORK

The application of soft computing techniques to dielectric constant estimation via free-space measurements has been presented. Results obtained are promising and demonstrate the validity of this approach.

GA and PSO show better performance for actual measurements if the error is not high. This approach can be used for real tests. On the other hand, ANNs present promising behavior in presence of high noise, although further improvement is needed.

Future work must include the training of networks with a set of actual measurements, and the experimentation with other architectures/topologies.

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