Enabling Antenna Design with Nano-Magnetic Materials using Machine Learning

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Abstract— **A machine learning approach to design with magneto dielectric nano-composite (MDNC) substrate for planar inverted-F antenna (PIFA) is presented. A new mixing rule model has been developed. A database of material properties has been created using several particle radius and volume fraction. A second database built with antenna simulations has been developed to complete the machine learning dataset. It is shown that, starting from particle radius and volume fraction of the nano-magnetic material, it is possible to calculate the antenna parameters like gain, bandwidth, radiation efficiency, resonant frequency, and viceversa with good precision by using machine learning techniques.**

Index Terms/Keywords — **Antenna, machine learning, magneto-dielectric nanomaterial.**

I. INTRODUCTION

An important field of research that is related to antenna design is the use of advanced materials which help to reduce antenna size and maximize antenna performance. These materials often have to be synthesized from first principles. An example of such materials are ferromagnetic nanostructures (nanoparticles, nanowires, nanoflakes…) that are included in dielectric layers to increase the permeability and permittivity values. Rather than using *ad-hoc* methodologies to synthesize such materials, mathematical models that are able to capture the behavior of these mixed materials are preferred. These mathematical models capture the underlying physics and provide a mapping from the particle and mixing details to the electrical properties of materials. These properties can then be used to design antennas. Even if the electrical properties are known, the process of designing the antenna is a laborious process since electromagnetic simulators need to be used which can be very time consuming.

II. PROBLEM DEFINITION

This paper starts examining the behavior of the magnetic material through experimental data and theoretical results coming from the Landau-Lifshitz-Gilbert (LLG) equation, both proposed in several papers, then evaluating eddy currents, ferro-magnetic resonance, magnetization saturation etc by taking into account the shape, size and characteristics of the material used. Then we analyze the behavior of the composite structure using mixing rule based models such as effective medium theory proposed by Bruggerman [1]. Here, we propose some new models that can be used. Since composite materials have within them small unevenly grouped elements, we consider a parallelepiped layer of dielectric material with inclusion of nanospheres of ferromagnetic material. This combination of materials allows, in certain limits due to the percolation threshold [1], the layers to maintain the property of insulation and at the same time to increase its permeability and permittivity values. We will not make direct reference to problems related to the percolation threshold in this articles. We will use a large volume fraction range to test the model.

The properties of the material that are required for antenna design are its permittivity, permeability and all associated dielectric and magnetic losses. Permittivity and permeability are dependent on many parameters. First of all, we must consider that the magnetic material and the dielectric one have different resonance frequencies. The magnetic material resonance frequency is closely related to the geometry of the particles embedded in the layer [2]. Other parameters to take into account are those intrinsic to the magnetic material such as gyromagnetic ratio, magnetization saturation, crystalline particles orientation, volume fraction, electric polarizability, temperature and frequency [2],[3],[4].

Understanding how to modify one or more of the parameters mentioned before, within certain limits, allows us to control values of permeability and permittivity. This can lead to significant advantages at the design phase for electronic structures. In this paper, a model has been developed where the input variables include the radius of the nanoparticles and their volume fraction in the dielectric, with other parameters held constant. These two parameters represent the controllable parameters during material synthesis.

Through simulations, a database was created, where the output are the electrical properties of the material such as permeability, permittivity, electric and magnetic loss tangent. Since, the antenna needs to be designed around 1 GHz, the electrical properties of the material needs to be stable at this frequency along with low dielectric and magnetic losses. Hence, the constant parameters were suitably controlled to ensure that the output electrical parameters had the desired properties for antenna design. For a set of nanoparticle dimensions and volume fraction, the models were validated using measurements [5] where Cobalt nanoparticles were mixed in a fluoropolymer dielectric.

In this paper we use the synthesized material to design a PIFA antenna around 1 GHz that is used in mobile applications. This requires extensive electromagnetic simulations. With the data obtained from the simulations of the antenna a second database was created. The two databases (one mapping the particle size/volume fraction to electrical property and the second mapping electrical property to antenna performances) were used as input and output for training a machine learning algorithm to create a mapping between the properties of the material used as the substrate and the antenna's performance.

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Machine learning has been used in the past for material synthesis [6], only for the electrical properties of the material. Here, we extend this approach to design antennas. For a set of input and output parameters, the antenna was designed and measured to validate the developed model [7].
Through machine learning it is now possible to determine the particle size and volume fraction required to achieve a desired set of antenna performance such as its operational frequency, bandwidth, gain and efficiency. Machine learning can also be used to create a sensitivity matrix that quantifies the effect of particle dimensions and volume fraction on antenna parameters.

III. MATHEMATICAL MODEL

First of all we need to define an analytical function to describe the behavior of the intrinsic permittivity and the intrinsic permeability of the nanoparticles.
A fundamental aspect then is to find a way to relate the size of nanoparticles with ferro-magnetic resonance. As proposed in [2], the following law has been used

$$\frac{\omega_{FMR}}{\gamma_0} = \frac{C\mu_{kn}^2}{R^2 M_S} + H_0 - \frac{4\pi}{3} M_S + \frac{2K_1}{M_S} \quad (1)$$

where ω_{FMR} is the resonant frequency, μ_{kn} is the eigenvalue of the equation $[J_n^{'}(r)]_{r=R} = 0$ with J_n being Bessel's spherical function, γ_0 is the gyromagnetic ratio, C is the exchange constant, R is the particles radius, M_S is the magnetization saturation, H_0 is the external magnetic field, K_1 is the magneto-crystalline anisotropy constant.
The relative complex permeability has been defined as

$$\mu_r(\omega) = 1 + \frac{\mu_{rLF} - 1}{1 - j\xi\, \omega/\omega_{FMR} - (\omega/\omega_{FMR})^2} \quad (2)$$

where μ_{rLF} is the relative permeability at low frequency and ξ is the damping ratio.
Material polarizability is given by the sum of more contributions due to different types of polarization [8]. Those contributions are given by the interface polarization, dipole polarization, ionic polarization and electronic polarization. Only the first three resonant frequencies will be considered in the final model because the fourth one is at too high frequency.
The equation that describes the behavior of the material polarization is the following

$$\rho(\omega) = 1 + \frac{(\rho_r - 1)\left(1 - \frac{\omega}{\omega_{int\rho R}}\right)\left(1 - \frac{j\omega}{\omega_{d\rho R}}\right)\left(1 - \frac{\omega}{\omega_{at^{\rho}R}}\right)^{fk}}{\omega\left(1 - jk\frac{\omega}{\omega_{d\rho R}}\right)\left(1 - j\xi\frac{\omega}{\omega_{i\rho R}} - (\frac{\omega}{\omega_{i\rho R}})^2\right)} \quad (3)$$

where ρ_r is the maximum value of the polarizability at zero frequency, $\omega_{int\rho R}$ represents the frequency limit of the contribution due to the interface polarization, $\omega_{d\rho R}$ represents the frequency limit of the contribution due to the dipole polarization, $\omega_{i\rho R}$ is the frequency at which there is resonance due to ionic polarization, k is used to adjust the width of the contribution due to dipole polarization, $(1 - \omega/\omega_{at^{\rho}R})^{fk}$ is used to control the overshoot and the subsequent oscillation, with fk is possible to adjust the slope of the function around $\omega_{at^{\rho}R}$ ($\omega_{at^{\mu}R}$ will be used in (7) for the same purpose).

Things get even more complicated when we want to know the electromagnetic behavior of a layer composed of more than one material.
Also the volume fraction, a parameter that identifies the volume ratio between two or more materials, plays an important role.
In our case we will have two materials, one dielectric, and the other ferromagnetic.
In literature it is often assumed that the effective permittivity and permeability of a composite material are governed by the same principle. Many mixing rule models have been proposed, but the most common are reported in the following [9]:

Maxwell Garnett Approximation (MGA)

$$\frac{\beta - 1}{1 + n_0(\beta - 1)} = p\frac{\alpha - 1}{1 + n_0(\alpha - 1)} \quad (4)$$

Bruggerman Effective Medium Theory (EMT)

$$p\frac{\alpha - \beta}{\beta + 1 + n_0(\alpha - \beta)} = (1 - p)\frac{\beta}{\beta + 1 - n_0\beta} \quad (5)$$

And Landau-Lifshits-Looyenga (LLL) [7]

$$(\beta + 1)^{1/3} - 1 = p((\alpha - 1)^{1/3} - 1) \quad (6)$$

where

$$\alpha = \varepsilon_i/\varepsilon_h - 1 \leftrightarrow \alpha = \mu_i/\mu_h - 1$$
$$\beta = \varepsilon_e/\varepsilon_h - 1 \leftrightarrow \beta = \mu_e/\mu_h - 1$$

In the above equations, ε_i is the intrinsic permittivity of nanoparticles, ε_h is the permittivity of the matrix medium, ε_e is the effective permittivity of the composite material, μ_i is the intrinsic permeability of nanoparticles, μ_h is the permeability of the matrix medium, μ_e is the effective permeability of the composite material, n_0 is the depolarization or demagnetization factor (for spherical shape $n_0 = 1/3$), p is the volume fraction.
From the simulations of the three above models it can be seen, even using identical input, that they differ from each other in the description of the behavior of a composite material. It is also almost impossible to tune these models with experimental data as there are no parameters to do it. For these reasons a new model has been defined.
A non-ferromagnetic material has a value of relative permeability equal to 1; then the contribution to the permeability of the composite material depends exclusively on the quantity of ferromagnetic material present within the layer.
It is expected that the function of the permeability of the entire layer converges asymptotically to 1 at high frequency.
Therefore model in *(2)* has been modified as

$$\mu(\omega) = 1 + \frac{(\mu_{rLF} - 1)\cdot p^{DF}\cdot(1 - \omega/\omega_{at^{\mu}R})^{fk}}{(1 - j\xi\, \omega/\omega_{FMR} - (\omega/\omega_{FMR})^2)} \quad (7)$$

where DF is a parameter denoted as dominant factor, which adjusts the contribution of the magnetic material according to the volume fraction. Behavior of (7) is shown in Fig. 1.

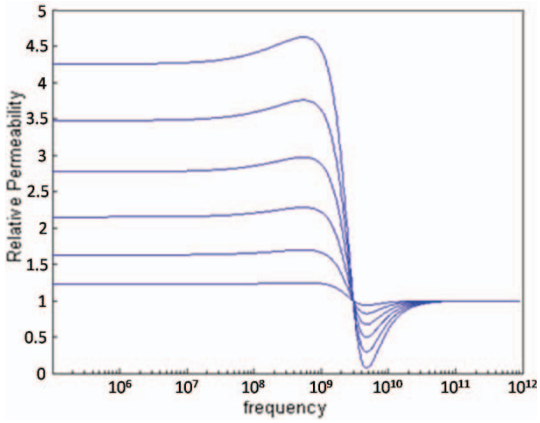

Fig. 1. Real Part of (7) with $p = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6$. (Frequency is expressed in Hz).

However, for permittivity things are different. Furthermore, inserting particles of ferromagnetic material within a dielectric material alters its polarizability, by increasing it [10]. Therefore, the equation which describes the behavior of the permittivity will be composed of two parts, one describing the relative contribution of the dielectric material to the polarizability and the other for the polarizability of the magnetic material.

The equation that describes the behavior of the relative complex permittivity (Fig. 2) is the following

$$\varepsilon_r(\omega) = 1 + \frac{(\rho_{rm}-1)p^{DF}(1-\omega/\omega_{at^{\mu}R})^{fk}}{(1-j\xi\,\omega/\omega_{FMR}-(\omega/\omega_{FMR})^2)^{kc}} + \qquad (8)$$

$$+\frac{(\rho_{rd}-1)(1-p)^{(DF-1)}\left(1-\frac{\omega}{\omega_{int\rho R}}\right)\left(1-\frac{j\omega}{\omega_{d\rho R}}\right)^{kc}\left(1-\frac{\omega}{\omega_{at^{\rho}R}}\right)^{fk}}{\omega\left(1-jk\frac{\omega}{\omega_{d\rho R}}\right)^{kc}\left(1-j\xi\frac{\omega}{\omega_{i\rho R}}-(\frac{\omega}{\omega_{i\rho R}})^2\right)}$$

where kc is a parameter used to control the slope of the graph.

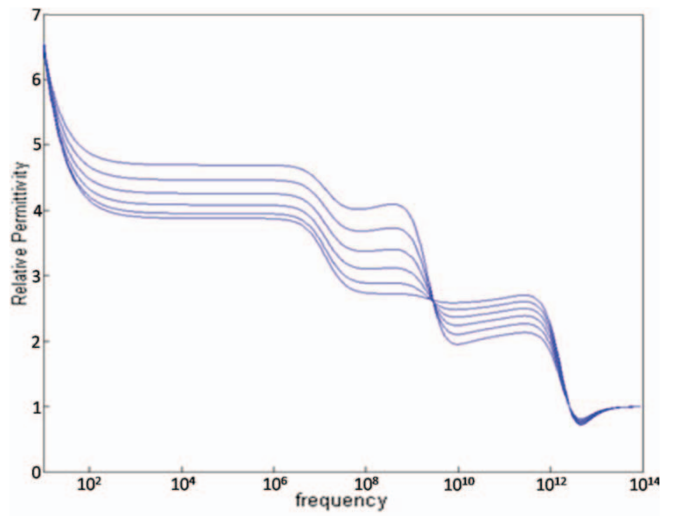

Fig. 2. *Real Part (8)* $p = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6$. (Frequency is expressed in Hz).

Until now it has been considered that all particles have the same diameter. In an actual case, however, there is no technology capable of producing nanoparticles with absolute precision with same size. What is reasonable to consider is that we will have an average diameter and a probability distribution of Gaussian type (Fig. 3) around the average value [11].

The equation which identifies the density of probability is the following

$$d(r) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{r-r'}{\sigma}\right)^2\right) \qquad (9)$$

where r' is the nanoparticles radius expected value and σ is the corresponding variance.

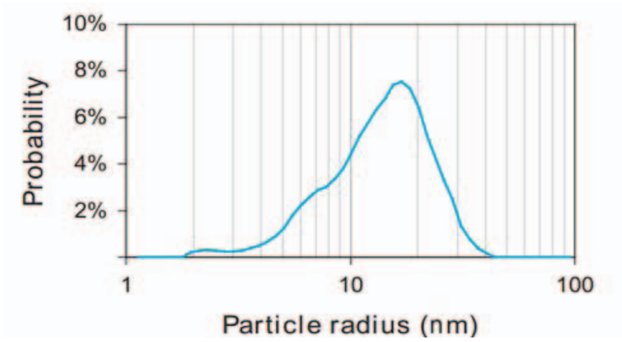

Fig. 3. *Particles radius probability [11]*

The model has been implemented taking into account the particles radius probability. What happens is that the peak due to the ferromagnetic resonance is more rounded than before. The effect may be explained by the fact that now there is no longer a single frequency of ferromagnetic resonance, but related to nanoparticles various sizes we will have a set of resonances in a limited range of frequencies.

IV MACHINE LEARNING

The first step of machine learning is the construction of a dataset. In order to reduce mapping error, use of a large amount of data is strongly recommended [12].

A set of permittivity, permeability and the associated dielectric and magnetic losses values were obtained using (7) and (8) by varying particle radius and volume fraction. A 42 samples database, which we will call Database A, was created.

As a second step, a set of simulations were performed using the PIFA proposed in [7] which was designed to work around 1 GHz. Fig. 4 shows the antenna geometry, which was fabricated and measured.

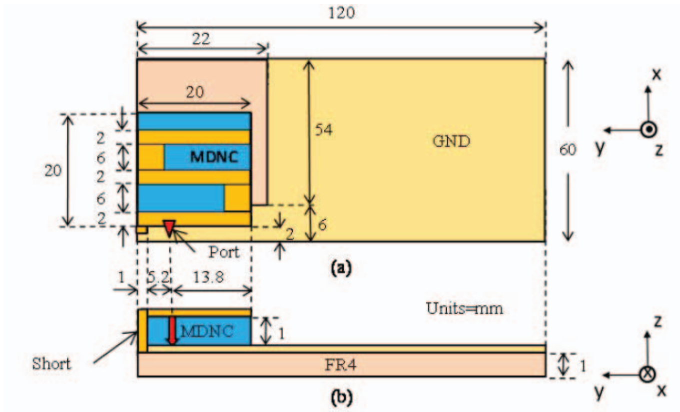

Fig. 4. Geometry of the proposed PIFA on Magneto-dielectric nano-composite (a) top view and (b) side view [7]. Dimensions are expressed in millimeters.

Values from Database A have been used to define Magneto-dielectric nano-composite (MDNC) substrate material properties.

A second database called Database B has been created using CST [7] an antenna design software.
It contains the antenna parameters like gain, bandwidth, radiation efficiency and resonant frequency. The calculation required more than 15 minutes for each simulation using a workstation with double processor and 48 GB of RAM. For the neural network learning process, the Bayesian Regularization algorithm was used with ten hidden layers, with the number of hidden neurons arbitrarily chosen by the algorithm. Bayesian Regularization algorithm was chosen because it showed the best performance for our dataset between several other learning algorithms.

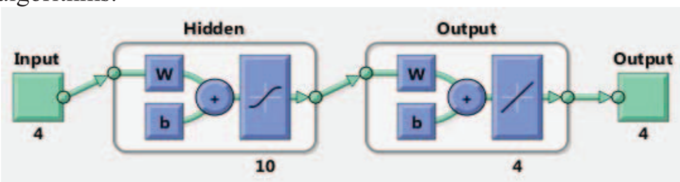

Fig. 5. Network Structure

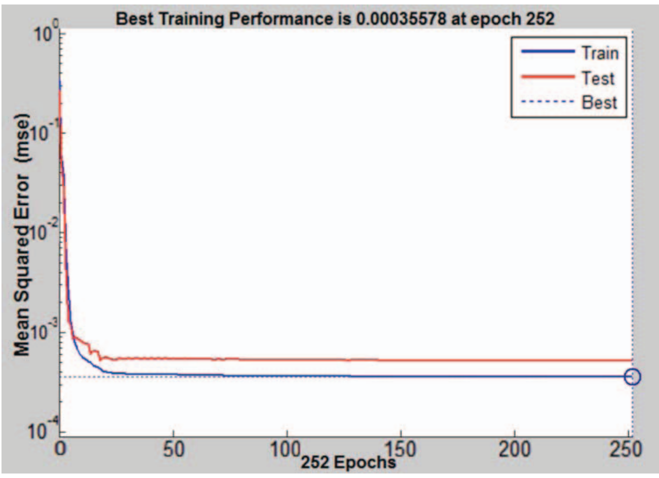

Fig. 6. Epochs cardinality for the squared error curve

Epochs (repetitions) means the number of iterations made by the Learning Algorithm to reach convergence (Fig. 6).
After the learning process, the neural network has been used to make an oversampling on the Database B, bringing the samples from 42 to 322 in a few seconds.

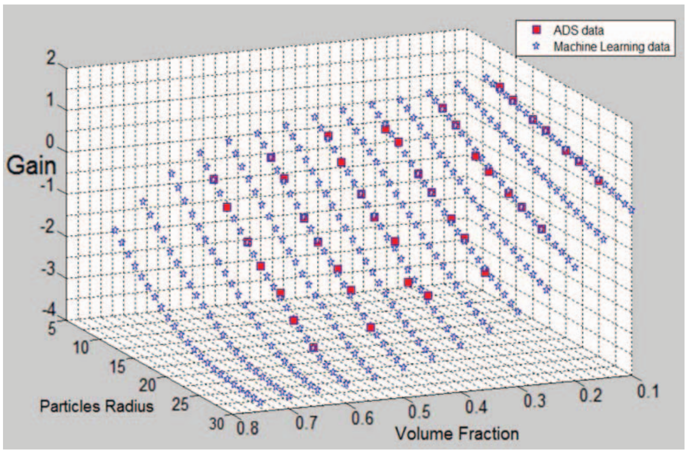

Fig. 7. Red squares represent data regarding antenna's gain from CST, blue stars represent data from machine learning. Radius size is expressed in nanometers.

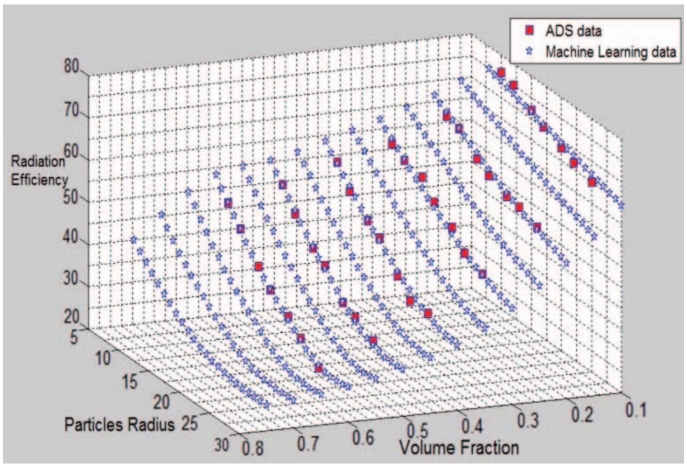

Fig. 8. Red squares represent data regarding antenna's radiation efficiency obtained from CST, blue stars represent data from machine learning. Radius size is expressed in nanometers.

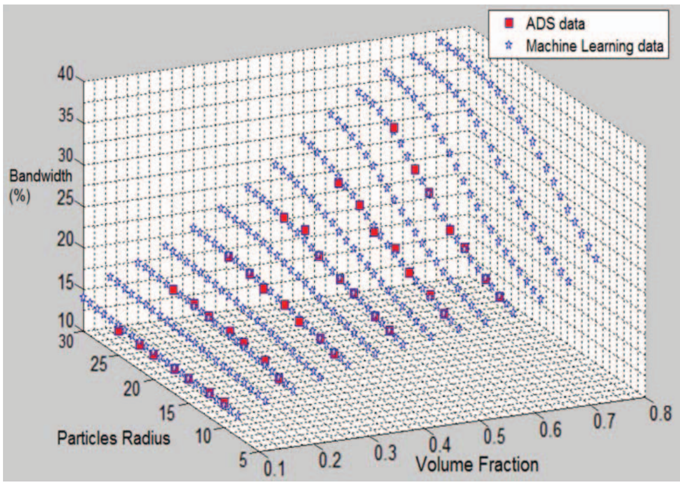

Fig. 9. Red squares represent data regarding antenna's bandwidth obtained from CST, blue stars represent data from machine learning. Radius size is expressed in nanometers.

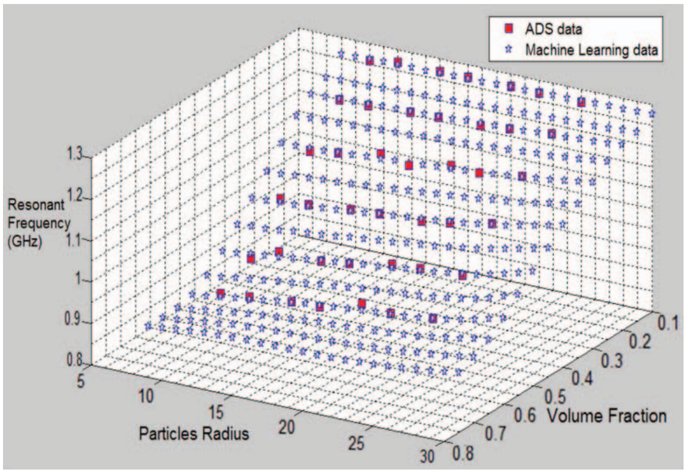

Fig. 10. Red squares represent data regarding antenna's resonant frequency obtained from CST, blue stars represent data from machine learning. Radius size is expressed in nanometers.

Fig. 7 to 10 show that the data from Machine Learning follow the trend of the antenna design software data.

We can now associate the antenna parameters to the corresponding material properties. In this way it is possible to predict the behavior of the antenna knowing its substrate characteristics or trace back to the particles dimensions starting from the performance of the antenna.
The error has been calculated between data from Database B and corresponding machine learning data.

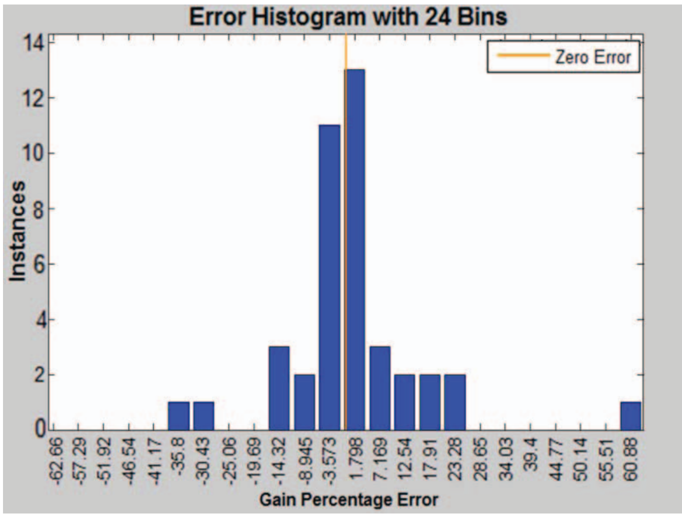

Fig. 11. Histogram shows on the x-axis the gain percentage error between target and machine learning output and number of instances on y-axis

In Fig. 11, it is clearly seen that a large error (7% of total) is found only for a few isolated instances. An explanation of this resides in the fact that a database with 42 samples is too small to perform an effective learning process; a second reason is that the antenna gain values are positive and negative and at the same time close to zero, so percentage error looks large although the absolute error is relatively small.

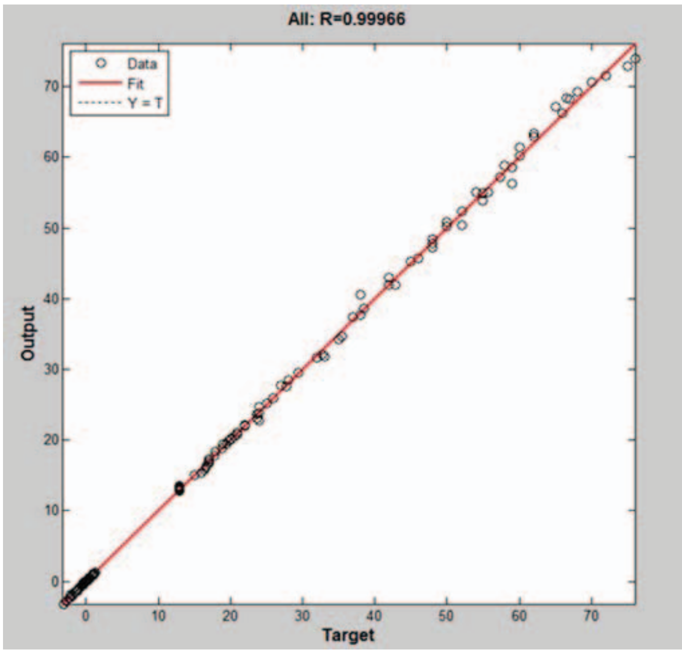

Fig. 12. Machine Learning Output – target (all of the data stored in Database B) regression curve. Data concern Gain, Radiation Efficiency, Bandwidth and Resonant Frequency.

The dashed line represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. As is shown in Fig. 12 the solid line is completely overlapped with the dashed line so the fit is very good for this machine learning problem, the R value is close to 1, it means the output of our network can follow strictly input variations.

V. CONCLUSIONS

A machine learning approach to design antennas has been presented. We made a new mathematical model to calculate complex permittivity and permeability of a magneto dielectric material and used those in an antenna design software to define antenna substrate. These were then used to simulate the performance of the antenna.
The results presented show the usefulness of the machine learning technique to reduce the cycle time for the synthesis of new materials, minimize the error and extend the use of machine learning for designing antenna with new nano-composite materials.

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