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***Abstract*—In the exploding growth of radio mobile and wireless communication applications, microstrip antennas with its advantages of low cost and flexible fabrications, emerge as the most suitable candidate. The direct antenna synthesis could, however do not result in the optimal antenna configuration, and therefore a possible alternative is considering the problem of optimizing the antenna as a system of uncertainty, in which each set of geometrical parameters returns a totally different response; the best set, i.e. the one that gives the best antenna performances, can be obtained using global optimizers, as evolutionary algorithms. The main drawback of this approach is that it is really time and memory consuming. In this article, a technique based on the hybridization between Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN)is introduced with the aim of reducing this nimerical cost and implemented to optimize a dual-annular ring proximity coupled feed antenna.**

***Index Terms*—artificial neural network, evolutionary algorithm, microstrip antenna**

I. Introduction

Since modern communication systems demand high quality data service, bandwidth enhancement of printed antennas has become a vital study over the last two decades. The easiest way to reach this scope is that of using mere than one radiating element, generally located on different dielectric layers. This technique could however results in defining a quite complex structure; moreover, in some applications a reduced antenna thickness is required, and therefore the use of radiating elements located on the same dielectric layer and eventually fed by electromagnetic coupling with a microstrip line printed on a lower layer, is more convenient. Among the single-layer configurations with enhanced bandwidth presented in literature there are several that combine different shape annular patches, located one inside the others: in this way it is possible to have a compact, multi-resonant structure. The first type of annular patch considered in literature was the circular one (see for instance[1] and references therein). The advantage of structures with different patches is not only that they allow a bandwidth enhancement, but also that they present different geometrical parameters that could be properly selected in order to optimize the antenna performances [2], [3].

However, with the complexity of the structure to be optimized also the computational cost and the memory occupation required by the optimization increase. With the aim of reducing both of them, authors have investigated in the past years the possibility to adopt a surrogate model, base on the use of an Artificial Neural network (ANN), that, once trained, behaves as the antenna under optimization, requiring lower computational and memory effort [4]. This methodology as illustrated in Figure 1, so-called Regular sampling, was clearly explained in [5]. In [4], [5], the conventional optimization scheme, was employed and it was proved to save a significant amount of computational resources. With the aim of reducing committed error level, a new solution of multiple neural networks instead of one network is presented in [7]. In those aforementioned approaches, all steps are executed separately [11], [10].

The initial idea of new training scheme and its effectiveness were presented on dual rectangular ring structure in [6]. In order to overcome this limitation, a new hybrid method is proposed, by imposing ”smooth combination” between global optimizer and ANN. The main difference relays on the way the optimizer retrieve data: arbitrary data set from unsatisfied configurations instead of formally chosen in the range of interest. In order to test the effectiveness of the developed scheme, it is here applied to the optimization of a proximity coupled fed dual annular ring antenna.

II. Electromagnetic problem and optimization tools

A. *Antenna of the test*

In order to investigate the robustness of the hybrid technique, a proximity coupled fed type antenna is chosen as a test object. This multi-layer structure consists in two concentric annular rings situated on the top layer, the feeding microstrip line in the middle layer and the ground plane on the bottom layer.

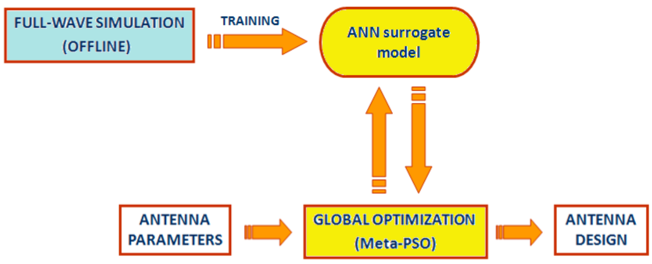

Fig. 1. Old optimization scheme by Regular training.

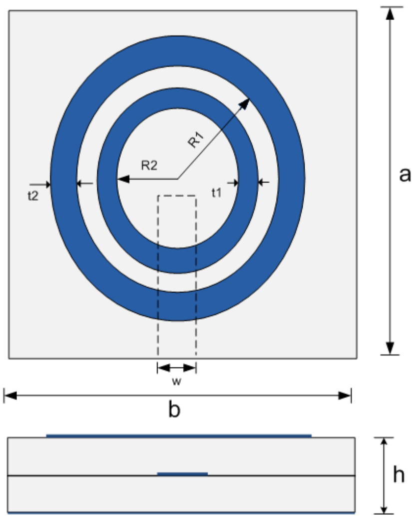

Fig. 2. Top view and side view of the test object antenna.

All these structures are printed on FR4 substrate with dielectric constant ε_r = 4.4 and height of 2.4 mm for each layer. The main object of the optimization scheme is to enlarge as much as possible the bandwidth over the requested WIFI band (2.4 GHz to 2.5 GHz). As illustrated in Figure 2, six geometrical parameters namely a, b, R_1, R_2, t_1, t_2 could vary in a specific range of interest. Fabrication constraint and feasibility of the structure are also taken into account, and this means, for example, that, since the two concentric rings cannot overlap each other, the outer ring cannot exceed the region of the patch.

III. Interpretation of Hybridization Technique

The main idea of the proposed technique is to utilize the data from unsatisfying antenna configurations as prior knowledge for the ANN training. ANN is a self-adaptive modeling tool that changes its structure on the basis of external or internal information flowing through the network. Therefore, more information is updated, more accurate outputs the ANN surrogate model can provide. The crucial difference between this hybridization technique and the conventional ANN used in [5] is the way in which the training set data retrieved. The proposed ANN simulates the behavior of the radiating structure at the varying of the Frequency, together with the six geometrical parameters already mentioned above, i.e. a, b, R_1, R_2, t_1, t_2 and uses two hidden layers of 9, 7 neurons respectively. This architecture ends up with two outputs: the real part and the imaginary parts of the Return Loss, as illustrated in Figure 3. At the end, the two outputs are recombined to form the amplitude of Return Loss, which is the main concern of global optimizer.

IV. Numerical Results and Conclusions

In order to prove the efficiency of the proposed method, it has been compared with the conventional ANN model. In Figure 4 the magnitude of the return Loss computed with the here proposed technique and with the traditional ANN scheme are plotted versus frequency f, since antenna structures are investigated in the band of interest (from 1.5 GHz to 3.5 GHz) with the resolution of 400 steps, and the geometrical parameter b that has been discretized by 7 samples. The rest of antenna parameters are fixed as: a = 30 mm; R_1 = 12 mm; R_2 = 5 mm; t_1 = 1.5 mm; t_2 = 1.5 mm. The color bar, ranging from 0 to 0.2, indicates the error introduced by ANN approximations in conventional scheme [5] and in proposed hybrid method. As can be seen from the plots, the error committed by Irregular sampling method is slightly higher than Regular one. The maximum error value recorded is 0.1 and this difference can be neglected. The primary purpose is a better control by obtaining training data from arbitrary sets of inputs rather than formally chosen space so that the total time consumption is saved radically.

TABLE I
Comparison of computational effort between conventional and hybridization technique.

Sampling technique	Number of samples	Computational time
Regular	$5^6 = 15625$	25 days
Irregular	450	17 hours

As shown in Table I, according to scheme in [5], in order to create training set data, 15625 samples are needed. The proper ANN architecture for this huge data set might not be found. Provided that it exists, the amount of time for training is tremendous and it would lead the surrogate-based optimization by ANN to impractical. By employing this hybridization technique, the case of over-training data is eliminated by a set of constraints and loops. Regarding this particular case, the total amount of time spent is 17 hours, much less than estimated 25 days of conventional scheme. These results confirm the effectiveness of the proposed scheme, making it extendable to more complex electromagnetic problems.

TABLE II
Optimized geometrical parameters by ANN model when being integrated with PSO optimizer.

Parameter name	Value (mm)
a	40.13
b	39.92
R_1	12.7525
R_2	6.6776
t_1	3.9319
t_2	3.7056

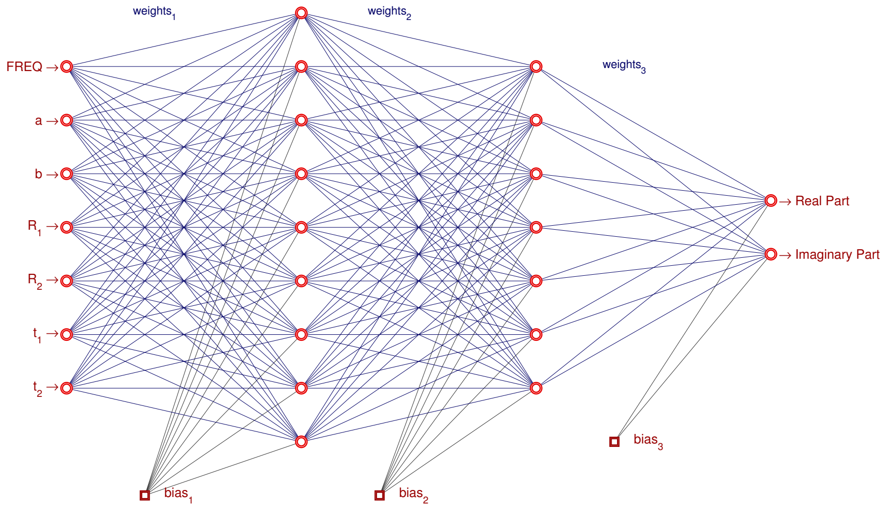

Fig. 3. Artificial Neural Network Architecture.

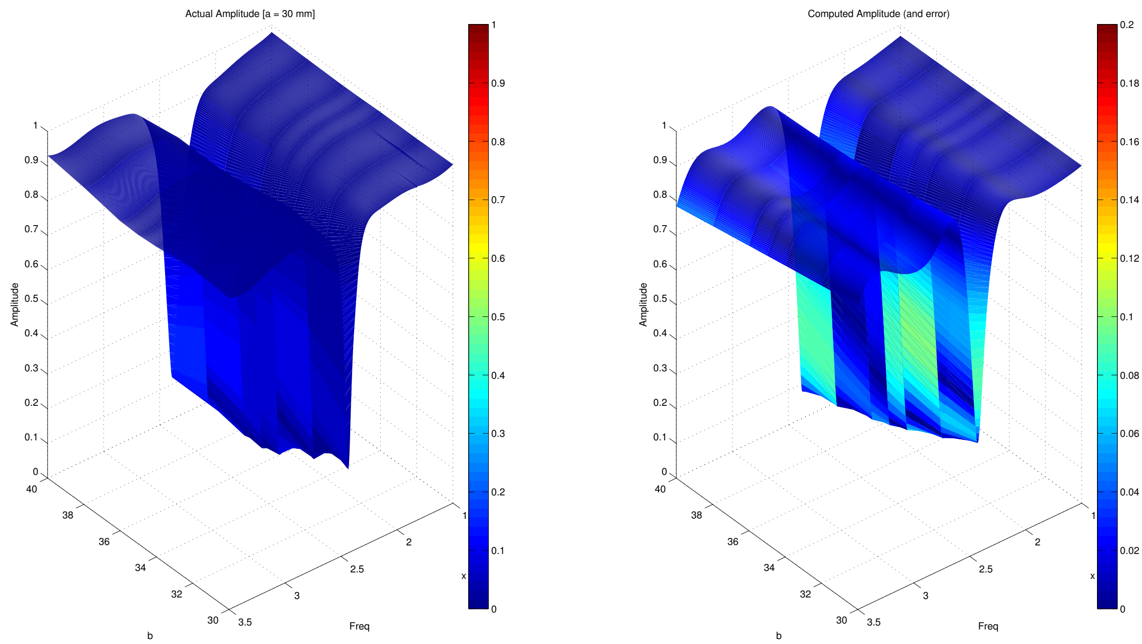

Fig. 4. Numerical efficiency comparison between conventional and hybridization technique according to the change of frequency f and b.

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