Use of an Artificial Neural Network-based metamodel in the optimization by Particle Swarm Optimization method

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***Abstract*— This study aims to develop efficient techniques for optimization of electromagnetic problems. We use the PSO algorithm (Particle Swarm Optimization) associated with a metamodel based on an ANN (Artificial Neural Network). Specifically, we use the MLP (Multilayer Perceptron) with the backpropagation algorithm. The ANN will be used to assist the technique of "*quasi* 3D" ray-tracing in order to reduce the high computational cost of this technique in PSO optimization.**

***Index Terms*— Artificial Neural Networks, Multilayer Perceptron, electromagnetic fields, Particle Swarm Optimization, metamodeling.**

I. INTRODUCTION

An important application of metamodels is in the optimization of electromagnetic problems. In fact, given that the modeling of such problems generally have a high computational cost, the optimization of electromagnetic devices often require certain procedures for the replacement of objective functions, in order to evaluate them in an efficient way. The replacement function allows obtaining results with good precision, but with a much lower computational cost [1].

Several models can be used to obtain approximations of objective functions with good accuracy. The kriging model [1] and the feed-forward neural network, for example, are robust and offer savings in computational time. Studies have shown that these two metamodels have similar performance [2]. Therefore, we chose to use the Artificial Neural Networks (ANN), which has been widely used in several applications due to ease of implementation and effectiveness.

It is important to stress that the evolutionary algorithms associated with metamodels are becoming extensively used by a growing number of researchers in design optimization [3]. Here, we show the validity of the PSO (Particle Swarm Optimization) algorithm in conjunction with an ANN-based metamodel to be used in the optimization of electromagnetic problems.

II. USE OF THE PSO AND ANN IN OPTIMIZATION

In order to verify the effectiveness of the PSO algorithm assisted by an ANN, this approach was initially used in the optimization of a test function. Specifically, the goal is to find the global maximum of the function Peaks, given by the equation (1):

$$F(x,y) = 3(1-x)^2 e^{-x^2-(y+1)^2} - \left(2x - 10x^3 - 10y^5\right) e^{-x^2-y^2} - \frac{1}{3} e^{-(x+1)^2-y^2} \quad (1)$$

It also implemented a case study presented in [4], corresponding to the propagation of an electromagnetic wave in an indoor environment, of 40 m × 28 m, whose ceiling height from the ground is 3 m. The goal is to find the best placement of two antennas in order to have the best environment coverage. A relevant aspect is that this case study refers to a problem with continuous search space, which is permitted placement of antennas in any position within the environment and not just at specific points. It was defined a grid of 160 reception points uniformly distributed within the environment. The antennas at all the reception points were considered to be 1.5 m high from the ground.

The goal of this implementation is to test the effectiveness of the PSO optimizer using an ANN (network MLP with backpropagation algorithm) as a metamodel.

Another important aspect in defining the topology of neural network is the number of neurons in the hidden layer, due to its influence on both the speed and the effectiveness of the learning network, which was defined by the geometric mean between the input and output neurons [5].

The neural network was used in order to replace the calculations made by the quasi 3D technique, [4], [6].

The neural network through supervised learning characteristic of Multilayer Perceptron with backpropagation algorithm optimizes weight values that are saved in a file. With these weigh values, the ANN calculates the field at each reception point. These field values are used by the PSO optimizer, which will obtain the optimal positions of the antennas and the corresponding received power mapping.

III. RESULTS

The optimization was done both directly using the function given in equation (1) and using an ANN-based metamodel to represent it. In both cases, the PSO was used to obtain the global maximum location, represented by particle "×" in Fig. 1. The algorithm was initialized with a random set of particles and the process took place until the maximum point was located, at the center of the red contours.

In the first case, we consider an optimization problem with analytical solution. Figure 1 shows the function that was simulated using an ANN-based metamodel in the optimization by PSO method. Figure 2(a) shows the contour plot of the results obtained using directly equation (1) while figure 2(b) shows the results obtained using the ANN simulating the function given in (1).

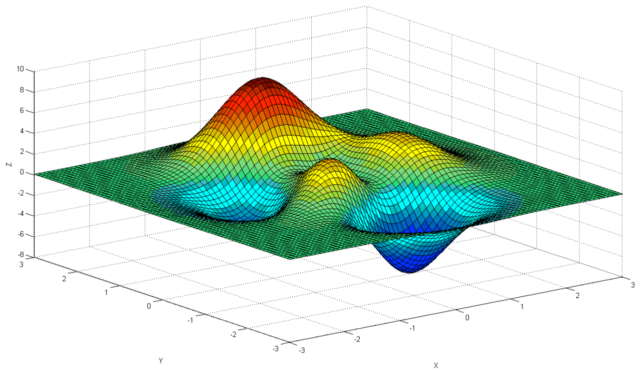
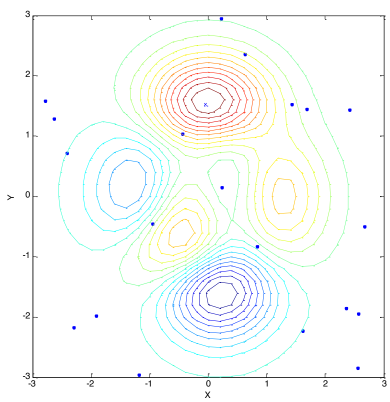


Fig. 1. The analytical function considered.



(a)

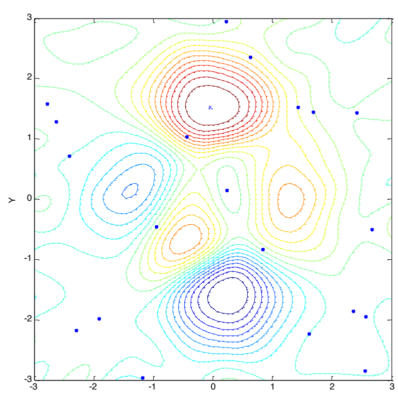


Fig. 2(a). The contour plot of the actual function; (b) The contour plot of the simulated function, with the located peak.

The ANN was trained until a root mean square error of 0.0004 was obtained, requiring 27,253 epochs to get this error value. The mean square error solution of PSO assisted by the ANN was equal to 0.00569. Analyzing the results, we can conclude that the use of a metamodel to replace the original fitness function allows obtaining good results.

In the second example, we analyzed a real problem: the optimization of two antennas placement in an indoor environment. Figure 3 shows the result of PSO assisted by ANN, aiming to replace the ray tracing "*quasi*-3D" simulation, which has high computational coast. The graph shows the placement of two antennas in order to supply the needs of 160 receivers as described in section II. The PSO assisted by RNA was initialized with a set of 50 random particles. The optimization was set to happen in 3000 epochs, under the conditions presented.

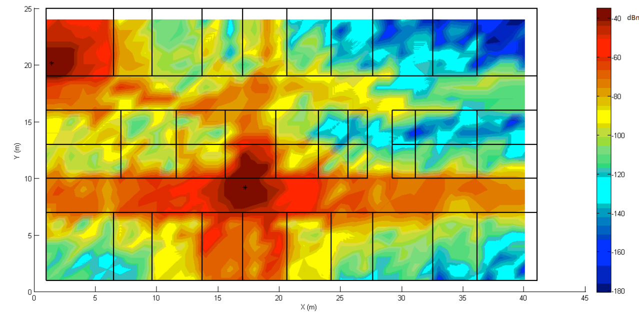


Fig. 3. Received power mapping in the indoor environment.

IV. CONCLUSIONS

In the optimization of an electromagnetic problem, the computational cost can be very large, since it is necessary to carry out a numerical simulation for each evaluation of the fitness function. In this case, the use of an ANN as metamodel permits to obtain satisfactory results with a significant reduction of the computational cost

In this paper, we proposed a PSO optimizer assisted by an ANN. In order to assess its effectiveness, it was applied in a test function with a global maximum. Also, it was applied this approach in an electromagnetic problem (namely, the best antenna positioning in wireless systems). The response of the ANN-assisted PSO for a real electromagnetic problem can be considered very good, but not necessarily the best, since with more training, time can get closer to the best response. The proposition for the extended paper is to reach the optimal time training to achieve a satisfactory response. New results as well as more details and discussions will also be presented in the full paper.

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