Multi-Net ANN approach for improving antenna optimization

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Abstract

In recent years, evolutionary algorithms have been successfully adopted for the optimization of various electromagnetic problems. One of the most common electromagnetic application is in the framework of microstrip antennas, thanks to the advantage of being low cost and low profile. In order to reduce the computational effort of the electromagnetic optimization, a suitable equivalent model by ANN has been created in order to substitute the commercially available full-wave analysis solvers. In this article, a new solution for multiple-output problem is presented. All the concepts will be integrated into the optimization of multi-layer proximity coupled feed microstrip antenna. Numerical results and efficiency have been reported in order to enlighten the effectiveness of the proposed approach.

1. Introduction

Thanks to the advantage of being low-cost and low-profile, microstrip antenna has been successfully adopted in a wide range of applications. In the literature, typical proximity coupled-feed microstrip antennas have been carefully studied by full-wave spectral analysis in [1]. The dual rectangular ring configuration, reported in Figure 1, yields more degrees of freedom to the designers but introduces in the same time more complexity. This structure has been first optimized in [2], and later on has been considered as an electromagnetic (EM) benchmark for comparing the effectiveness of different optimizers in [3]. In order to reduce the computational effort, a fast and accurate model has been first introduced in [4], where this simplified equivalence has been embedded and directly managed by global optimizers. In [4], ANN systematic pattern has been trained by a Gradient Descent Method: the well-known Error Backward Propagation. In this context, the aforementioned antenna becomes the benchmark test for the proposed approach to deal with a typical EM problem, in terms of effectively managing both the non-linear complexity and the ANN dimensions and characteristics. A new solution where separated neural networks in order to reduce error commited by the surrogate model have been adopted is here proposed. The implemented training rule is the Second-derivative Levenberg-Marquandt algorithm. The new proposed approach shows significant improvements both in terms of time convergency and accuracy. All the numerical results will be presented in detail in the next sections.

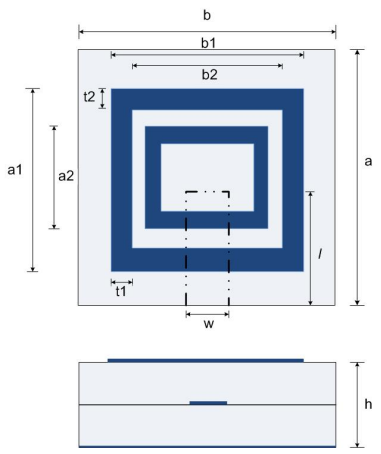

Figure 1: Top view and side view of the test object antenna

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2. Optimization tool and artificial neural network

Sampling the target data and using the neural networks are two discrete steps. Regarding this "Regular methodology", the desired outputs have been obtained by a full-wave analysis from formally chosen geometrical inputs in the possible region of interest. For each parameter 5 values have been considered, and more variables to be optimized also means that the needed training set grows exponentially, as reported in Table 1

Table 1: Computational cost for different problems

Assessments	3 inputs	4 inputs	5 inputs
Number of samples	25	125	625
Time consumption	40 mins	3.5 hour	18 hours

The knowledge extracted from physical models may be used as the target data for training the Artificial Neural Network. After being trained successfully, the so defined ANN will be employed as an equivalent model in order to substitute the full-wave analysis. Since ANN architecture only deals with binary and simple activation function, this surrogate model saves a critical amount of execution time with respect to very complex even commercialy available or in house university developed electromagnetic solvers. The best results ever found by ANN will be validated by full-wave analysis in order to check the accuracy of the simplified model.

3. Artificial Neural Network

An artificial neural network consists of a pool of simple processing units (neurons or cells) which communicate by sending signals to each other over a large number of weighted connections [5]. It is also known that ANN is a self-adaptive modeling tool that changes its structure on the basis of external or internal information that flows through the network during the learning phase [6]. For instance, in [7] a neural network-based solution has been carried out to predict the phase characterization of reflect waves by varying the size of radiating elements.

Error Backward Propagation (EBP) is based on the gradient descent algorithm [8]. EBP propagates error backwards through the network to allow the error derivatives for all network weights to be efficiently computed. In other words, network weights are optimized in order to reach a good and accurate output and this objective is reached typically minimizing the mean-squared error between the networks output, $f(x_i)$, and the target value y_i over all the N example pairs. To test the ANN generalization capability, a Validation Set (VS) is defined too, containing known (x_i, y_i) pairs not used in the Training Set (TS), in order to check the correct association between unknown input and output data. In general, Backpropagation algorithms update weights between layers based on the gradient of error function:

$$E = \frac{1}{2}\|f(x,i) - y(i)\| \tag{1}$$

3.1. Levenberg-Marquandt Training

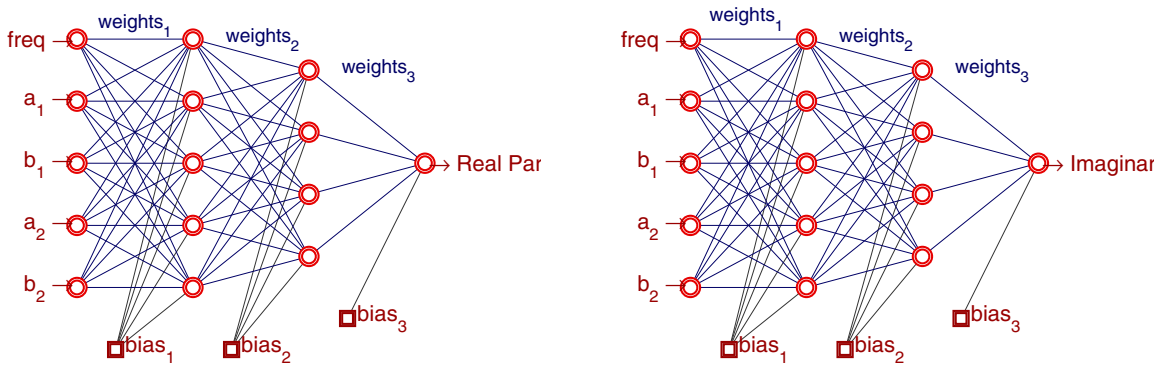
However, when dealing with large-scale problem with huge amount of data set, EBP algorithm is not adequate to handle that kind of sophisticated problem. In order to tackle this issue, a second-order algorithm namely Levenberg-Marquandt (LM) is adopted [9]. LM algorithm uses second-order derivative of total error function for weight updates. In this technique, the Hessian matrix, which gives the proper evaluation on the change of gradient vector. In order to simplify the calculating process, the LM makes the approximation of Hessian matrix by means of Jacobian Matrix:

$$H \approx J^T J + \mu I \tag{2}$$

where I is the identity matrix, J is the Jacobian Matrix, μ is always positive, called combination coefficient. The update rule of LM method can be derived as:

$$w_{k+1} = w_k - \left({J_k}^T J + \mu I\right)^{-1} J_k e_k \tag{3}$$

Training is a time and memory consuming process and it is the most critical phase in the ANN setup. Therefore, a new solution by separating neural networks for different outputs is provided. In order to check out the robustness of proposed method, numerical comparisons are presented in the next section.



(a) ANN for the Real Part

(b) ANN for the Imaginary Part

Figure 2: Two separated neural networks

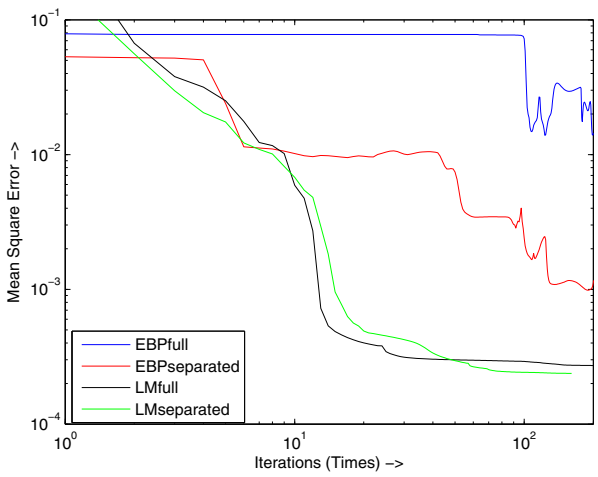


Figure 3: Training error level as a function of number of iterations versus proposed methods.

3.2. Splitted Neural Networks

In this optimization scheme, first reflection coefficients are retrieved by full-wave analysis and then they are used as training set data for ANN training.It is also worth noting that antenna radiation is a lossy process and return loss is always a complex number. It is separated into two part: Real and Imaginary before being recombined to produce Amplitude which is the main interest in terms of bandwidth optimization problem. In stead of one network of two outputs, we separate it into two distinguished networks with one output for each: Real and Imaginary Figure 2. The dimension of splitted neural network is reduced: 5,4 neurons for first and second hidden layer respectively. By reducing the dimension of neural network architecture, we also save more training time.

4. Numerical results and conclusions

Figure 3 illustrates the robustness of proposed method: LM training for two separated network. For what concerns the EBP algorithm, the division of NN decline significantly error committed to the value of 0.001. However, as reported in Figure 3, LM is proved to be more effective in minimizing the error grade. Both full network approach and separated one demonstrate the great improvement in solution accuracy. The best result is achieved by implementing LM-2 outputs.

The effectiveness of a proper ANN has been observed, considering both its numerical efficiency and the error introduced by the model. After the optimization run, the resulting geometrical configurations are validated by full-wave

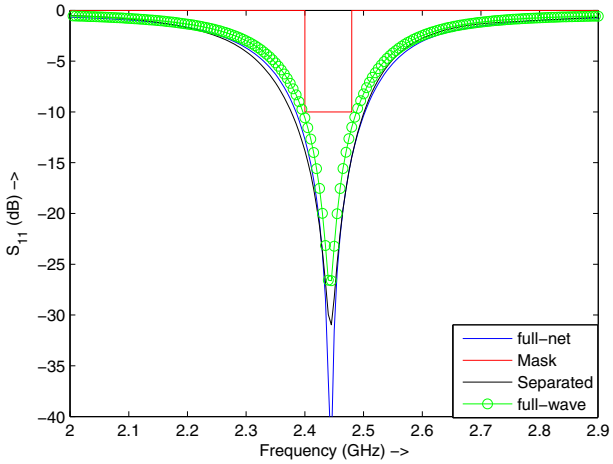


Figure 4: ANN optimization and full-wave analysis validation.

analysis. Figure 4 shows the comparisons between the different uses of ANN (by LM training). It demonstrates that all proposed methods have a good match with target data. However, the 2 output approach exhibits a better performance since the output data is closer to outputs since the absolute difference between the target data and ANN outcome is just 0.0005.

Regular Method of extracting information for training Neural Network may exceed the required amount of data. The future research will concentrate on imposing conditions for reducing the computational time and memory storage effort for the ANN learning.

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