Applications of Modular RBF/MLP Neural Networks in the Modeling of Microstrip Photonic Bandgap Structures

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Abstract—This paper presents a Radial Basis Function/Multilayer Perceptron (RBF/MLP) modular neural network, training with the Resilient Backpropagation (Rprop) algorithm which has been used for nonlinear device modeling in microwave band. The proposed modular configuration employs three or more neural networks, each one with a hidden layer of neurons, and aim to take advantage of the MLP and RBF networks specific characteristics to improve learning aspects, such as: ability to learn, speed of training and learning with consistency, or generalization. Simulations through the proposed neural network models for microstrip line with anisotropic PBG (Photonic Bandgap) structure and a metallic enclosure microstrip with PBG gave responses in good agreement with accurate results (measured or simulated) available in the literature.

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1. INTRODUCTION

Since the beginning of the 1990s, the artificial neural networks have been used as a flexible numerical tool, which are efficient for the RF/microwave device/circuit modeling. The neural models, which are trained by means of precise data (obtained through measurements or by electromagnetic simulation), are used in the design/optimization phase of devices and circuits, supplying fast and accurate responses. In the CAD (Computer Aided-Design) applications related to microwave engineering and optical systems, the use of ANNs as nonlinear models becomes very common, [1]. Some hybrid modeling techniques have been proposed for the use with empirical models and neural networks, such as: Source Difference Method, [2], PKI (Prior Knowledge Input), [3], KBNN (Knowledge Based Neural Network), [4] and SM-ANN (Space Mapping Artificial Neural Network), [5]. A disadvantage in the hybrid models usage is the need of an empirical model. When this becomes a limitation, for example, when a new component does not have an empirical model or an equivalent circuit, the EM-ANN (Electromagnetic-Artificial Neural Network), [1] conventional technique, is commonly utilized. In this case, a simple neural network, MLP or RBF, is trained directly through electromagnetic data, which represent the behavior of the component under analysis.

In this paper the RBF/MLP modular structure is composed by combination of two expert RBF networks and one output MLP network and that configuration has been used for modeling devices in microwave/optical bands [6, 7]. The development of models through the RBF/MLP modular structure is described in Section 2. The applications of these neural models for microstrip line with anisotropic PBG (Photonic Bandgap) structure and a metallic enclosure microstrip with PBG are presented in Section 3. Section 4 gathers the conclusions of this research.

2. METHODOLOGY THROUGH THE RBF/MLP MODULAR STRUCTURE

The proposed modular structure uses three feed forward neural networks, each one with a hidden neuron layer: two expert RBF networks and an output MLP network. Figure 1(a) illustrates a diagram in RBF/MLP modular structure blocks. This choice was motivated by the individual characteristics of the MLP and RBF networks when used in the function approximation learning tasks: the RBF network performs a local approach, serving as an expert network, since it grasps the models’ nonlinearities; the MLP network performs a global approach and acts as an output network, since it favours the generalization capacity of the RBF/MLP modular structure. In this technique, the model input parameters, named by ‘initial value’ and ‘intermediary value’, are related to the interested region defined by the training data, Figure 1(b). In order to receive additional information supplied by the pre-trained expert RBF networks, the output MLP network has two extra inputs, as shown in Figure 1(a).
Figure 1: (a) The proposed modular network configuration, (b) interest region defined by the training dataset.

The modeling problem mentioned is established by means of a normalized set of measured/simulated data, cited by $S = [x(n), d(n)]$, where, $1 \leq n \leq N$, and $N$ is the total number of examples in the $S$ training dataset. The $x$ vector gathers the parameters of the model input (for instance, the geometrical parameters of microstrip line filters and frequency). The $d$ desired response describes the device EM/physics behavior under consideration (for instance, the frequency response and scattering parameters). The EM/physics theoretical relation between $x$ and $d$ is given by,

$$d = f(x)$$

(1)

where, $f$ represents the input-output relation, which can be multidimensional and highly nonlinear. The aim is to develop a fast and accurate neural model for the $f$ relation. The neural model is defined through the relation,

$$y = y(x, w)$$

(2)

where, $w$ represents the free parameters (or weights) of the neural network structure.

The use of the RBF/MLP modular structure enables the division of a modeling problem in smaller and easier problems to be solved. To describe this division, the interested region is taken into account defined through the training data for a hypothetical device, Figure 1(b). The data referred to the ‘initial value’ and the ‘initial value’ parameters are used in the training of #1 and #2 expert RBF networks, respectively; the training of the MLP output network is done with all the training dataset, including the ‘intermediary values’ available.

In the MLP and RBF network supervised training with the backpropagation algorithm [8], the adjustment of the weights is carried out through the steepest descent method,

$$w(t) = w(t - 1) - \eta \nabla E(w(t - 1))$$

(3)

where, $\nabla$ is the gradient operator; $\eta$ is a training parameter, called learning rate, which controls the adjustments applied to the weights; and $E$ is the square error of instantaneous error between the desired response and the neural network output. The training is carried out until the mean square error $E(t)$ reaches a minimum pre-established value. The $E(t)$ is a parameter that measures the training algorithm performance, and is defined by,

$$E(t) = \frac{1}{N} \sum_{n=1}^{N} E(n)$$

(4)

where, $t$ is an index for the number of training epochs. An epoch is counted when all the training examples are presented to the neural network.

Due to the fact that backpropagation learning is too slow for many modeling applications, in this work the use of the Rprop algorithm (using the standard training parameters) is chosen [9]. The Rprop algorithm, proposed by Riedmiller and Braun [9], belongs to the algorithm family derived from backpropagation, which satisfies Jacobs’ heuristics for the training acceleration, [10]. In the ANN training using the Rprop, just the gradient signs of the error function, Eq. (3), are
taken into account. The negative influence elimination of the gradient amplitudes in the Eq. (3) is eliminated, as well as the use of adaptive and individual learning rates for each ANN free parameter, awards convergence speed and robustness as regards the choice of the training parameters of Rprop algorithm, [9].

3. NEURAL NETWORK MODELING APPLICATIONS

3.1. Microstrip Line with Anisotropic Planar PBG

The anisotropic uniplanar PBG is a microstrip structure with a ground plane consisting of an array of etched slots of alternating widths, as shown in Figure 2(a). Its pattern is a two-dimensional (2-D) square-lattice periodic structure with a unit cell geometry exhibiting a 180° symmetry. When the line is in the \( z \)-direction, the induced current can flow freely through the structure and the signal is transmitted, while the signal is rejected when the line is in the \( y \)-direction because of the stepped-impedance slots breaking the continuity of metal paths [11].

![Figure 2: (a) Microstrip line with PBG anisotropic structure, (b) ground plane of the anisotropic PBG structure with parameters.](image)

For the results presented in this paper, the period is \( a = 1.524 \text{mm} \) and the substrate is RT/Duroid with \( h = 0.635 \text{mm} \) and \( \varepsilon_r = 10.2 \). The total dimensions of the PBG are, therefore, \( L_y \times L_z = a(N_y \times N_z) = 1.524(N_y \times N_z) \text{mm} \), where \( N_y \) and \( N_z \) are the number of unit cells along \( y \) and \( z \), respectively, as shown in Figure 2(b). In this particular case, \( N_z \) is fixed in 7, \( N_y \) vary 1 to 7 and line is placed in AD direction.

In the neural model training for the anisotropic planar PBG, two scaled input parameters were taken into consideration: the operation frequency, \( f \), and the number of cell on \( y \) axis, \( N_y \). The measured values in the scattering parameter \( S_{21} \) make up the desired responses for the neural models. The training data were obtained through measurements presented in [11]. The information related to the RBF/MLP modular network training is presented in Table 1.

<table>
<thead>
<tr>
<th>Neural Network</th>
<th>Expert 1-RBF</th>
<th>Expert 2-RBF</th>
<th>Output-MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input parameter:</td>
<td>( N_y = 1 )</td>
<td>( N_y = 7 )</td>
<td>( N_y = [1 7] )</td>
</tr>
<tr>
<td># hidden neurons:</td>
<td>15</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td># training examples:</td>
<td>84</td>
<td>84</td>
<td>168</td>
</tr>
<tr>
<td>final ( E(t) ):</td>
<td>5.86E-005</td>
<td>7.42E-004</td>
<td>1.62E-004</td>
</tr>
<tr>
<td># training epochs:</td>
<td>2000</td>
<td>1500</td>
<td>2000</td>
</tr>
</tbody>
</table>

Figure 3(a) presents the results obtained from simulation of the RBF/MLP modular model developed. A good agreement between this model’s responses and the measured data is verified, with excellent interpolation to the training dataset examples. To take account of this highly nonlinear learning task, a reasonable generalization result was obtained around what permits to predict the filter stop-band approaches to microstrip anisotropic PBG, as shown in Figure 3(b).
3.2. Metallic Enclosure Microstrip Line with PBG

To observe the influence of a metallic enclosure on the $S$-parameters of a PBG structure with holes etched in the ground plane, the PBG circuit proposed in [12], is analyzed as the basic PBG structure in current section. In this case, a PBG circuit with five unit cells is fabricated on TACONIC CER-10 (dielectric constant $\epsilon_r$ of 10) substrate with the thickness $h = 1.5748$ mm, as shown in Figure 4. Other lattice dimensions $a = b = 2.5$ mm, $g = 0.2$ mm, and a period $d = 5$ mm. The gap, whose length is the same as the width of the strip line, is just located under the strip line in the metallic ground plane. A line width of 1.46 mm is used, corresponding to 50 Ω line for a conventional microstrip line, [13]. The aim of this section is to analyze and to model the influence in terms of the distance between the lower wall of the metallic enclosure and the PBG structure.

Table 2: Information related to the RBF/MLP modular training for the enclosure microstrip line with PBG.

<table>
<thead>
<tr>
<th>Neural Network</th>
<th>Expert 1-RBF</th>
<th>Expert 2-RBF</th>
<th>Output-MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input parameter:</td>
<td>$h_2 = 1h$</td>
<td>$h_2 = 6h$</td>
<td>$h_2 = [1h \ 2h \ 6h]$</td>
</tr>
<tr>
<td># hidden neurons:</td>
<td>10</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td># training examples:</td>
<td>31</td>
<td>31</td>
<td>93</td>
</tr>
<tr>
<td>final $E(t)$:</td>
<td>1.67E-004</td>
<td>1.64E-004</td>
<td>9.02E-005</td>
</tr>
<tr>
<td># training epochs:</td>
<td>3000</td>
<td>1000</td>
<td>5000</td>
</tr>
</tbody>
</table>

In the neural model training for the enclosure microstrip line, two scaled input parameters were
taken into consideration: the operation frequency, $f$, and the distance between the lower wall and the PBG ground plane, $h_2$. The simulated values in the scattering parameter $S_{21}$ through finite-difference time-domain (FDTD) method make up the desired responses for the neural models. In the model development for the enclosure microstrip line, the RBFs and MLP modular structure networks were trained separately. The relevant information for the training is in Table 2.

Figure 4(b) presents the results obtained from simulation of the RBF/MLP modular model developed. A good agreement between this model’s responses and the simulated data is verified, with excellent interpolation to the training dataset examples. To take account of this difficult nonlinear modeling learning task, a good generalization result is obtained in all considered frequency range, as shown in Figure 5.

4. CONCLUSIONS

In this paper a modular structure of neural networks, named RBF/MLP trained with the efficient Rprop algorithm, is developed for specific for utilization in stop-band filters modeling. In particular, a microstrip line with anisotropic PBG and enclosure microstrip line with PBG are used in modeling simulations.

The RBF/MLP structure’s modules are organized in order to take advantage of the local and global characteristics presented by the RBF and MLP neural networks, respectively, when used in the function approximation learning tasks. This kind of organization, together with the modeling problem division, becomes easier in the training of individuals RBF and MLP networks in the RBF/MLP modular structure. The obtained neural models simulation results indicate a good learning consistency, or generalization, and a major reliability of the models developed through the RBF/MLP modular structure. Besides, the RBF/MLP structure, directly trained by means of measured/simulated data through the EM-ANN technique, becomes very flexible, and it still can be applied as models, mainly when new components/technologies for microwaves circuits arise.

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REFERENCES