A hybrid neural model for the characterization of a single layer SIW waveguide

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Abstract: In this work, a hybrid neural model (HNM) able to characterize accurately the dispersion behavior of the fundamental $TE_{10}$ mode of a single layer SIW waveguide, is developed. The HNM combines the analytical expression that models the dispersion characteristics of this guiding structure, with a Multi Layer Perceptron Neural Network (MLPNN) which operates as an estimator of the cutoff angular frequency $\omega_t$ of the fundamental mode. The comparison among HNM computations, numerical results obtained with methods proposed in literature and full-wave data validate both the accuracy and the effectiveness of the proposed approach.

Keywords: CAD, Artificial Neural Network, SIW waveguide

Classification: Microwave and millimeter wave devices, circuits, and systems

References

1 Introduction

Substrate Integrated Waveguides (SIWs) preserve most of the advantages of the conventional rectangular metallic waveguides joining with a reduced cost of realization. SIWs are nowadays a consolidated technology for realizing circuits and devices operating in a frequency band ranging from microwave to Tera-hertz region [1, 2, 3]. Very recently, a method able to analyze these structures in an efficient way, based on the dyadic Green’s function and the Method of Moments technique, has been proposed [4, 5, 6, 7]. Despite of this, the design and the optimization processes of SIW devices still remain time consuming tasks. To reduce the related computational burden, the development of the so called “smart models”, based on the computational intelligence approach, have emerged as a powerful technique [8]. As far as SIW structures are concerned, this approach was adopted in [9] to evaluate the resonant frequencies of lossless SIW resonators and in [10] to develop an efficient design procedure for these devices. In this work, an approach based on a Hybrid Neural Model (HNM) [11, 12] able to model the dispersion characteristics of the fundamental $TE_{10}$ mode of a single layer SIW waveguide, for a range of electrical and geometrical parameters of practical engineering interests [5], is presented. The HEN combines the analytical model that describes the dispersive behavior of a SIW waveguide (which exactly coincides with that of a metallic rectangular waveguide [14]), with a Multilayered Perceptron Neural Network (MLPNN) which supplies the analytical model with an accurate estimation of the cutoff angular frequency $\omega_c$ of the fundamental mode of the structure at hand. To show both the accuracy and effectiveness of the proposed approach, numerical results relevant to the dispersive behavior of a single layer SIW waveguide have been compared with those obtained with the
Fig. 1. Single layer SIW waveguide: a): geometry; b): unit-cell representation.

empirical approaches proposed in literature [14, 15] and with data obtained with the commercial full wave code HFSS.

2 Cutoff frequencies of a SIW waveguide

Fig. 1 (a) shows the geometry of a single layer SIW waveguide. Due to its periodicity, the characteristics properties of this device can be deduced by its unit-cell representation (see Fig. 1 (b)) [14, 16]. Exploiting the two dimensional multi-port method developed in [16], the cell’s impedance matrix \( Z \), at an assigned angular frequency \( \omega \), can be computed numerically. If \( v_{\text{in}}, i_{\text{in}}, v_{\text{out}}, i_{\text{out}} \) are the \((1 \times N)\) input and output voltages and currents vectors related to the cell’s ports, with \( N \) the number of modes considered, we have

\[
\begin{pmatrix}
Z_{\text{in,in}} & Z_{\text{in,out}} \\
Z_{\text{out,in}} & Z_{\text{out,out}}
\end{pmatrix}
\begin{pmatrix}
i_{\text{in}} \\
i_{\text{out}}
\end{pmatrix}
=
\begin{pmatrix}
v_{\text{in}} \\
v_{\text{out}}
\end{pmatrix}
\tag{1}
\]

where \( Z_{\text{in,in}}, Z_{\text{in,out}}, Z_{\text{out,in}}, Z_{\text{out,out}} \) are sub-matrices when \( Z \) results partitioned, each having dimension \((N \times N)\). In term of \( Z \), the unit-cell’s chain matrix \( ABCD \) can be formulated as

\[
\begin{pmatrix}
ABCD_{\text{in,in}} & ABCD_{\text{in,out}} \\
ABCD_{\text{out,in}} & ABCD_{\text{out,out}}
\end{pmatrix}
=
\begin{pmatrix}
Z_{\text{in,out}}^{-1}Z_{\text{in,in}} & Z_{\text{out,in}}^{-1}(Z_{\text{in,in}}Z_{\text{out,out}} - Z_{\text{in,out}}Z_{\text{out,in}}) \\
Z_{\text{out,in}}^{-1} & Z_{\text{out,out}}^{-1}
\end{pmatrix}
\tag{2}
\]

By applying the Floquet’s theorem, and taking into account that the unit-cell is both a reciprocal and symmetrical circuit, the following eigenvalue equation can be obtained [16]

\[
T(\omega)i_{\text{in}}(\omega) = \lambda(\omega)i_{\text{in}}(\omega) \quad \text{with} \quad n \in 1, \ldots, N
\tag{3}
\]

where \( T = Z_{\text{in,out}}^{-1}Z_{\text{in,in}} \) and \( \lambda = \cosh(\gamma_np) \), from which the characteristic propagation constants \( \gamma_n \) of the SIW waveguide can be determined. The
SIW’s angular cutoff frequencies $\omega_i$ are the values for which $\gamma_n(\omega_i) = 0$ holds, or, equivalently, the angular frequencies $\omega_i$ satisfying the following relation

$$\det(T(\omega) - U) = 0$$

(4)

(where $U$ is the identity matrix) i.e., they are the non linear eigenvalues of the matrix operator $T(\omega) - U$ [17]. A computationally effective method to compute these values is given in [17].

Fig. 2. Pictorial representation of a Hybrid Neural Model’s block scheme.

3 ANNs and hybrid neural models

Artificial Neural Networks (ANNs) are intensively employed to model microwave devices and circuits [8]. To this purpose, Feed Forward Multilayered Perceptron Neural Networks (MLPNNs) are often exploited [13, 18]: mathematically, a MLPNN can be modelled as

$$y = y(x, W)$$

(5)

where $x$ is the input data vector, $y$ is the output responses vector and $W$ is the weight matrix. The elements $w_{ij} \in W$ are chosen during training phase $T_p$, in which they are changed until a suitable cost function

$$E(W) = \sum_{p \in T_p} \left[ \frac{1}{2} \sum_{k=1}^{M} (\hat{y}_{pk} - y_k(W, \hat{x}_p))^2 \right]^{\frac{1}{2}}$$

(6)

results minimized [13]. In (6) the term into the square brackets is the least square error associated to the $p$th tuple $\{\hat{x}_p, \hat{y}_p\}, p \in T_p$, $y_k(W, \hat{x}_p)$ is the $k$th output of MLPNN corresponding to the input $\hat{x}_p$ and $\hat{y}_{pk}$ is the $k$th element of the output vector $\hat{y}_p$ [13]. The prediction ability of an ANN can be exploited in the so-called Hybrid Neural Models (HNMs) [11]. A HNM combines between them a mathematical function (usually named empirical expression or empirical model) representing knowledge about the problem at hand, with an ANN, making possible in this way a more accurate modelling of the physical phenomenon under study [11, 12]. Two are the kinds of possible HNM architectures: the first is based on the input knowledge (HNMIK) approach, the second is based on the space mapping (HNMSM) approach [11, 12]. In our study, we have focused our attention of this latter model. The block scheme of a HNMSM model is depicted in Fig. 2. Essentially, it consists
of an ANN which maps a set of values of one part of the space of the inputs parameters $X_2$ into a new set of values $X'_2$ which is given in input to the empirical expression (see. Fig. 2), improving in this way the accuracy of the empirical model at hand [11].

4 Numerical results

In order to model the dispersion characteristics of a single layer SIW waveguide, we have developed a HNMSMA composed by a Multi Layer Perceptron Neural Network (MLPNN) “assembled” with the classic analytical expression for the propagation constant $\beta$ in this structure [14, 15]

$$\beta = \sqrt{\varepsilon_r \varepsilon_0 \mu_0 \omega^2 \left[ 1 - \left( \frac{\omega_t}{\omega} \right)^2 \right]}$$

(7)

on the basis of the block diagram reported in Fig. 2. The MLPNN’s input parameters were: the via hole radius $a_0$, the pitch $p$, the dielectric constant $\varepsilon_r$, and the width $W$. The angular cutoff frequency $\omega_t$ of the fundamental $TE_{10}$ mode was the output. The ranges of variation of the inputs are shown in Table I.

<table>
<thead>
<tr>
<th>$a_0$</th>
<th>$p$</th>
<th>$W$</th>
<th>$\varepsilon_r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05 ÷ 0.8</td>
<td>0.1 ÷ 3.5</td>
<td>0.45 ÷ 0.55</td>
<td>2 ÷ 10</td>
</tr>
</tbody>
</table>

Table I. Ranges of the physical parameters for the single layer SIW waveguide (all geometrical dimensions are in millimeters).

Three set of data, one of training and the others of validation and testing, having 950, 325, and 65 tuples, respectively, were created by using the approach described in the previous section. Several MLPNNs’ architectures have been developed and tested exploiting the MATLAB framework. In term of Root Mean Square Error (RMSE), the best results have been obtained
Fig. 4. Comparison of the dispersion curves of a SIW waveguide ($W = 6.25\,\text{mm}$, $p = 1.8\,\text{mm}$, $\epsilon_r = 3.1$). Left: $a = 0.9\,\text{mm}$, Right: $a = 1.6\,\text{mm}$.

by an MLPNN architecture having two hidden layers composed by six and three neurons, respectively (RMSE $\approx 10^{-4}$), using the Levenberg Marquardt algorithm [13]. Fig. 3 shown the scatter plot obtained comparing the values of $\omega_t$ obtained by full wave simulations with the MLPNN estimations, which demonstrates the excellent network ability to model the input-output relationship present in the data. In Fig. 4 is reported the comparison among the dispersion curves calculated $i$) by using our HNM approach, $ii$) by means of the equivalent waveguide approach [14, 15] and $iii$) by the commercial full-wave code HFSS. The excellent agreement obtained between our approach and full-wave results confirms the ability of our HNM model to provide an accurate evaluation of $\beta$ above the whole range of the geometrical and electrical parameters considered for its training. It is notable that, once the MLPNN has been trained, the characterization of the guiding structure’s dispersive property is almost immediate.

5 Conclusions

In this paper, an effective approach to model the behavior of a single layer SIW waveguide based on a HNM based on the space mapping approach, is presented. Numerical results are consistent with full wave computations, confirming the robustness of the proposed approach. Once that the HNMSM model is trained, it can predict the dispersive behavior an assigned single layer SIW waveguide in a very fast and accurate way, providing a computationally cheap model to employ in surrogate-based methods [19] for electromagnetic devices optimization.