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ANALYSIS AND SYNTHESIS OF MULTILAYERED ELECTROMAGNETIC ANTIREFLECTOR USING NEURAL NETWORK

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I. Introduction

Many applications require a multilayered dielectric to use as an antireflector, i.e., a reflector with almost zero reflection coefficient. For example, a radar target coated with such an antireflector may reduce its radar cross section (RCS) [1]. Neural networks have been gained attention as a fast evaluation and optimization method. A proper neural network structure and learning algorithm will be advantageous to develop the neural network. Then, the well-developed network may be used to analyze and synthesize a multilayered antireflector.

In this paper, the plane-wave incidence at a multilayered dielectric slab has been studied by using the neural network. The network adopts a multilayered perceptron (MLP) structure. The learning algorithm is the backpropagation (BP), which is used to train the network. Four learning methods（the gradient, the conjugate gradient, the quasi-Newton and the Levenberg-Marquardt (LM) method）of BP algorithm are employed in this study. The results show that the LM method may be the most suitable one for the considered problem.

II. Formulations

A. Reflection coefficient formula

A plane wave is incident normally at a multilayered dielectric slab whose thicknesses are $d_1, d_2 \cdots d_N$, as shown in Figure 1.

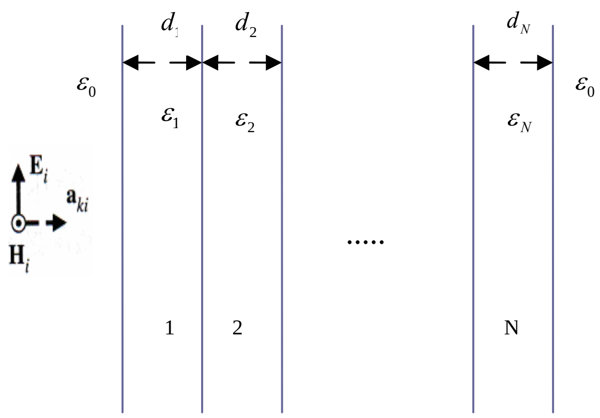

Figure 1. Plane-wave incidence at a multilayered dielectric slab

The reflection coefficient formula for the considered problem may be expressed as [1,2]

$$\Gamma_{in} = \Gamma_0 + \Gamma_1 e^{-j2\beta_1 d_1} + \Gamma_2 e^{-j2(\beta_1 d_1 + \beta_2 d_2)} + \cdots + \Gamma_N e^{-j2(\beta_1 d_1 + \cdots + \beta_N d_N)} \quad (1)$$

where

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$$
\begin{aligned}
\Gamma_0 &= \frac{\eta_1 - \eta_0}{\eta_1 + \eta_0} \\
\Gamma_1 &= \frac{\eta_2 - \eta_1}{\eta_2 + \eta_1} \\
\Gamma_2 &= \frac{\eta_3 - \eta_2}{\eta_3 + \eta_2} \\
&\vdots \\
\Gamma_N &= \frac{\eta_N - \eta_0}{\eta_N + \eta_0}
\end{aligned} \tag{2}
$$

η_0 is the intrinsic impedance for air, and η_N is the intrinsic impedance of the nth layer of the slab.

B. Neural Network Model

The model of neural network should be trained by learning the input data. After this learning, the neural network model will provide answer for the related problem. The MLP structure is adopted for the neural network. For learning algorithms, the BP algorithm is considered here. The BP algorithm consists of three layers: an input layer, a hidden layer and an output layer, as shown in Figure 2. Input layer contains N input parameters. Hidden layer contains input-to-hidden unit weights (w_{in}) and neurons. Output layer contains hidden-to-output unit weights (w_{ji}) and output parameters. Here, the neural network model relation is represented as [3],

$$y = F\left(\Sigma wx\right) \tag{3}$$

where F is a non-linear function, that may be a logistic sigmoid or hyperbolic tangent function.

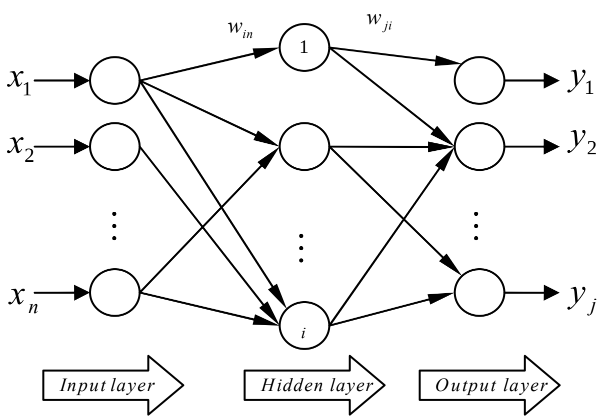

Figure 2. Basic form of a backpropagation algorithm

For this model, the error function is defined as a mean squared error (MSE)

$$E_{MSE}(w) = \frac{\sum_{j=1}^{J}\left(t_j - y_j\right)^2}{J} \tag{4}$$

where t_j is the jth element of the target output and y_j is the jth output of the neural network. Network learning process is to make this error function minimum. The error function may be changed according to the type or need of various problems.

The BP algorithm has many learning methods. Here, four methods have been introduced to use.

1.**Gradient**

The weights are expressed as

$$\Delta w_{n+1} = -\rho \left.\frac{\partial E(w)}{\partial w}\right|_{w=w_n} + \alpha\left(w_n - w_{n-1}\right) \tag{5}$$

where the weights are updated along the negative gradient direction. ρ is called the learning coefficient and α is the momentum coefficient. The weights are updated after all learning samples have been presented to the network.

2.**Conjugate Gradient**

Derived from quadratic minimization:

$$\begin{aligned} g_{n+1} &= g_n + \lambda_n H d_n \\ d_{n+1} &= -g_{n+1} + \gamma_n d_n \end{aligned} \tag{6}$$

where g is the gradient and d is called the conjugate direction. In addition, H is the Hessian matrix and γ is called the Fletcher-Reeves formula.

3.**Quasi-Newton**

The weights are updated using

$$\begin{aligned} w_{n+1} &= w_n - \rho B_n g_n \\ B_n &= B_{n-1} + \Delta B_n \end{aligned} \tag{7}$$

where B is the inverse of the Hessian matrix. ΔB_n is called the Broyden-Fletcher-Goldfarb-Shanno formula.

4.**Levenberg-Marquardt**

The weight formula for the LM method is

$$w_{n+1} = w_n - (J^T J + \mu I)^{-1} J^T r \tag{8}$$

where μ is a nonnegative number and r is a vector containing the individual error. In addition, J is the Jacobian matrix and I is the identity matrix.

III. Results and discussion

Using the four learning methods, i.e. the gradient, the conjugate gradient, the quasi-Newton and the LM method, the analysis and synthesis of the considered problem have been presented. At first, consider a single-layer slab. Calculate the thickness (d) when the values of frequency (f) and dielectric constant (ε) are given. Frequency begins from 1.1 GHz to 20 GHz and increases 0.5 GHz each time. The learning MSEs by the four learning methods are shown in Figure 3. We can find that the best of the four methods of BP algorithm is the LM method. In Figure 4, the output of the LM method is in good agreement with the target output. The total CPU time used by the LM method is around 25 seconds. CPU time is given for Pentium Ⅲ 1 GHz. Thus, the neural model is very fast to obtain the answer after learning.

As the reflection coefficient (Γ_{in}) is zero, find out the dielectric constant (ε) and the thickness (d). Consider a single-layer slab and lossy media (loss- tangent = 0.022). When the input frequency is 5.15 GHz and $\Gamma_{in} < 0.001$, the optimal values of ε and d have been obtained. The MSEs of the four learning methods are compared with each other, as shown in Figure 5. The best result is obtained by the LM method, the total CPU time is around 27.6 seconds. Consider a double-layer slab and lossless media. When the input frequency is 5.15 GHz and $\Gamma_{in} < 0.1$, the optimal values of ε_1, ε_2, d_1 and d_2 have been obtained as well. The values of the four learning methods are compared with each other, as shown in Table Ⅰ.

IV. Conclusion

To develop a promising neural network model needs an appropriate structure and an effective learning algorithm. In this paper, the MLP structure and the BP algorithm has been proposed and studied for analyzing and synthesizing a multilayered antireflector using neural networks. Four learning methods have been introduced to use. Among them, the LM method is the best one for the considered problem.

V. Acknowledgment

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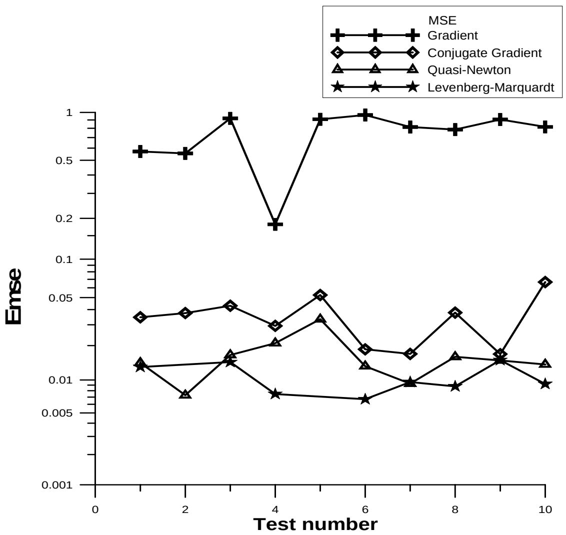

Figure 3. analysis - a single-layer slab – Emse

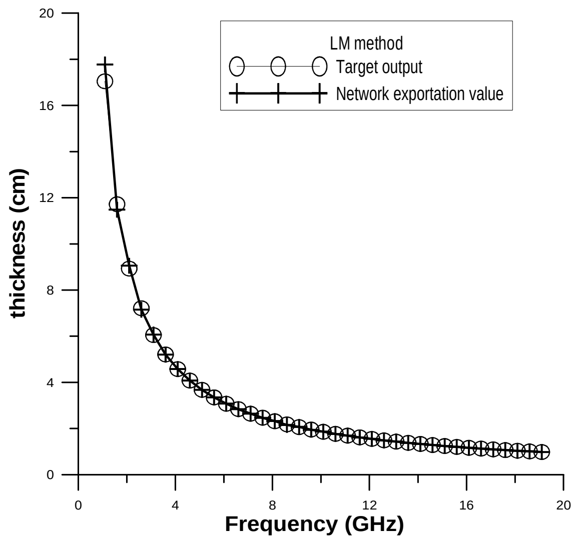

Figure 4. LM method, network exportation value compares with target output

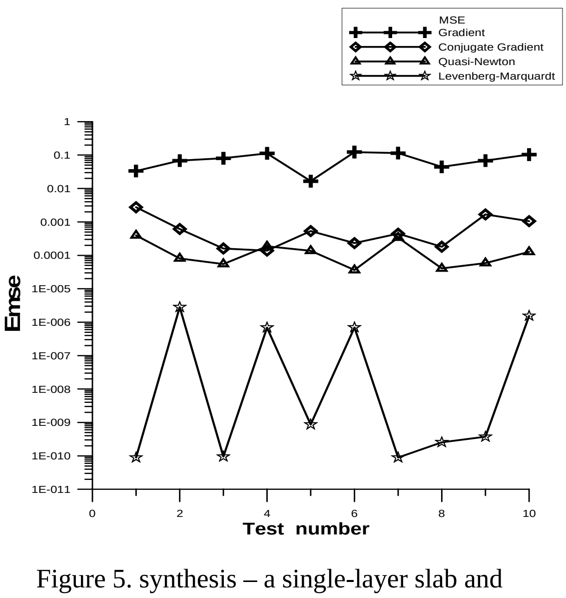

Figure 5. synthesis – a single-layer slab and lossy media

Table Ⅰ. Comparison of different learning methods

Train Method	ε_1	ε_2	d_1	d_2
Gradient	1.15	4.276	1.2191	0.66769
Conjugate gradient	1.1613	4.277	1.1477	0.69837
Quasi-Newton	1.1615	4.2786	1.1456	0.70453
Levenberg-Marquardt	1.16159	4.2796	1.1456	0.70396
Target output	1.16158	4.2790	1.1455	0.70394