Efficient Characterization of Microwave Applicator
Loaded with Multilayer Dielectric based on Neural Networks

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Abstract: In this paper, new neural network approach for characterization of cylindrical metallic cavity loaded with multilayer dielectric is suggested. Such cavity configuration has a great importance in realization of microwave resonant applicators, widely used for thermal processing of multilayer materials. Proposed neural model is based on representation of multilayer cavity load via several planparallel homogeneous dielectric slabs and superposition of separate influence of each dielectric slab parameters on the cavity resonant frequency. Model is incorporated into MLP neural network enabling its efficient implementation on modest hardware platform. Suggested approach is verified on the example of circular cylindrical metallic cavity loaded with two-layer dielectric.

Keywords: Microwave cavity, multilayer dielectric, neural network modeling, resonant frequency.

1 Introduction

EXTENSIVE use of microwave energy in industry, science and medicine has led to the development of a number of different microwave applicators. They come in various shapes and sizes based on the electromagnetic (EM) properties, geometry and volume of dielectric materials. Among them, the most popular ones

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are resonant applicators classified as either single or multimode cylindrical metallic cavities, partially loaded with dielectric slabs, widely used in the processes of material heating and drying. The knowledge of the mode tuning behavior in a cavity under loading condition (i.e. physical and electrical parameters of the load) forms an integral part of the studies in microwave heating and can significantly help in designing these applicators [1].

Multilayer dielectric is usual cavity load form when microwave resonant applicators are used for material thermal processing. Due to different layer structure of treated dielectric material and/or existence of plastic containers used as a support for material placement inside the cylindrical metallic cavity, it can be assumed that such cavity load has a form of several planparallel homogeneous dielectric slabs with different permittivity. Conventional approach for carrying a theoretical analysis of such loaded cylindrical metallic cavities is the transverse resonance method (TRM) [2]. Representing a loaded cavity as a cascade connection of the equivalent transmission lines, characteristic equation for resonance frequency calculation can be derived from the transverse resonance condition. In a general case, this equation is complex transcendental and its solution requires an appropriate numerical technique and an efficient mode identification procedure. Therefore, complex mathematical calculations are required, especially in the case of higher number of dielectric layers, which can be hardware and time consuming representing a main disadvantage of TRM.

Artificial neural networks represent a good alternative to the conventional approach in microwave heating area, allowing for equally accurate and faster calculation of resonant frequencies. Classical multilayer perceptrons (MLP) [3, 4] network, as one of existing artificial neural networks, has been applied very successfully for modeling of cylindrical microwave cavity applicators loaded with one-layer dielectric [5]. However, in order to achieve the acceptable accuracy in the process of loaded cavity resonant frequency determination, a large set of data was needed for training purposes of MLP models, leading to very difficult and time consuming process. In references [6–8], it was verified that the neural network modeling efficiency could be increased by incorporating an existing partial knowledge from problem domain into the neural model architecture. Such knowledge empirically derived or expressed through some known functional relations, comprising resonant frequency dependence on one-layer dielectric slab parameters was implemented into hybrid empirical-neural (HEN) network [3] or knowledge based neural (KBN) network [9]. Both neural models were capable to provide an accurate and efficient solution with more or less complex architecture depending on one-layer dielectric position inside the cavity.

However, for multilayer dielectric, as general cavity load form, representing via several planparallel homogeneous dielectric slabs with different permittivity,
dependence of loaded cavity resonant frequencies on multilayer dielectric geometrical and EM parameters becomes more complicated so that even partial knowledge from problem domain could not be easily extracted. Therefore, MLP network remains the only possible solution but such generated neural model has a very complex architecture with higher number of inputs and the same shortage of requiring a large set of training data which has to be provided by hardware and time consuming TRM approach for multilayer dielectric [10]. In this paper, alternative approach in neural network modeling of microwave cylindrical metallic cavity loaded with multilayer dielectric is suggested with the main goal to create more efficient neural model based on MLP network. New so-called hierarchical neural model is created on the basis of grouping some input parameters and their connecting through functional dependences that have an influence of determining a final relationship between model outputs and inputs. In the case of multilayer dielectric loaded cavity, this means that model is based on superposition of separate influence of each dielectric slab to the cavity resonant frequency, which leads to the reduced number of model input parameters and more efficient training procedure. Model accuracy and efficiency are illustrated through comparison with referent TRM results obtained for the case of resonant frequency determination of the TM112 mode in a cylindrical metallic cavity with circular cross-section and loaded with two-layer dielectric.

2 New Neural Approach for Multilayer Dielectric Loaded Cavity Modeling

Multilayer perceptron (MLP) neural network is high-parallel and high-adaptive feed-forward structure that is consisted of mutually connected neurons with nonlinear activation functions in hidden layers [3, 4]. Researches related to MLP application in microwave technique have showed that this network is able to approximate highly nonlinear functions with satisfactory accuracy and high level of generalization. A good characteristic of this network is that it belongs to the black box networks i.e. it is not necessary to know functional dependencies from the problem domain. MLP network allows for extraction of all functional dependences of the problem domain exclusively on the basis of the training data. Conventional MLP model of cylindrical metallic cavity loaded with N-layer dielectric is shown in Fig. 1 [10].

Its main limitation is that with the increase of number of dielectric slabs N, number of model input parameters increases according to law 2N (or 3N in a case when slabs are not supported by each other and if, for each slab, its elevation from the cavity floor is given). This leads to a very inefficient model training procedure.
Therefore, new hierarchical neural model is suggested in this paper. Its architecture consists of two levels. On the first level, there are basic MLP models (B-MLP) of the same structure which take into account an separate influence of each dielectric slab parameters (slab thickness \( t \) relative to the cavity height \( h \), \( t_h = t/h \), slab elevation from the cavity floor \( r \) relative to the cavity height \( h \), \( r_h = r/h \), and slab relative permittivity \( \varepsilon_r \)) on cavity resonant frequency:

\[
f_r^{(i)} = f'(t_{hi}, r_{hi}, \varepsilon_{ri}), \quad i = 1, 2, 3, \ldots, N
\]  

Second level contains generalized neural network (G-MLP) which, based on the found individual influence of each dielectric slab parameters, models the influence of all slabs together on resonant frequency of the cavity:

\[
f_r = f(f_r^{(1)}, f_r^{(2)}, \ldots, f_r^{(N)})
\]  

Therefore, hierarchical neural model practically describes functional relation:

\[
f_r = f(f'(t_{h1}, r_{h1}, \varepsilon_{r1}), f'(t_{h2}, r_{h2}, \varepsilon_{r2}), \ldots, f'(t_{hN}, r_{hN}, \varepsilon_{rH}))
\]  

For an example, for cylindrical metallic cavity loaded with two-layer dielectric placed at the cavity floor (represented by 2 planparallel homogeneous slabs, one immediately above the other), architecture of basic MLP model and new hierarchical neural model is shown in Fig. 2 and 3, respectively.

For that particular example, hierarchical neural model describes the following dependence:

\[
f_r = f(f_r^{(1)}, f_r^{(2)}) = f(f'(t_{h1}, 0, \varepsilon_{r1}), f'(t_{h2}, t_{h1}, \varepsilon_{r2}))
\]
where \( f_r^{(1)} \) is the resonant frequency when cavity is loaded only with dielectric slab 1 and \( f_r^{(2)} \) is the resonant frequency when cavity load is represented only by dielectric slab 2. Position of each dielectric slab is the same as in the case when they are both present inside the cavity.

Fig. 2. Basic MLP neural model that takes into account an influence of parameters of one dielectric slab.

Fig. 3. Hierarchical neural model of cylindrical metallic cavity loaded with two dielectric slabs.

The vector of \( l \)-th hidden layer outputs in B-MLP network and the output of the B-MLP network can be expresses as:

\[
y_l^B = F(ww_l^By_{l-1}^B + b_l^B) \tag{5}
\]

\[
f_{rMLP} = w_{rNHB}^B \tag{6}
\]

respectively, where \( B \) in superscript position denotes B-MLP network and \( N_{HB} \) is the total number of B-MLP hidden layers. In according with this, B-MLP part of hierarchical model can be described with the following general function notation:

\[
f_{rB-MLP} = f(x, W_{B-MLP}) \tag{7}
\]

where \( x \) represents vector of input variables in B-MLP network model, \( x = [t_r, \varepsilon_r, r_h]^T \), and \( W_{B-MLP} \) is a weight matrix of B-MLP network:

\[
W_{B-MLP} = \{w_1^B, \ldots, w_{N_{HB}}^B, w_0^B, b_1^B, \ldots, b_{N_{HB}}^B \} \tag{8}
\]
General symbol of B-MLP model is $\text{MLP}^N_{HB} - N^B_1 - \cdots - N^B_i - \cdots - N^B_{HB}$ where $N^B_i$ is the number of neurons in the $i$-th B-MLP hidden layer.

Similarly to B-MLP network, the vector of $l$-th hidden layer outputs in G-MLP network and the output of the G-MLP network can be expresses as:

$$y^G_l = F(w^G_l y^G_{l-1} + b^G_l)$$  \hspace{1cm} (9)

$$f^G_{r-MLP} = w^G_o y^G_{NG}$$  \hspace{1cm} (10)

respectively, where $G$ in superscript position denotes G-MLP network and $N_{HG}$ is the total number of G-MLP hidden layers.

Therefore, generalized MLP network can be described with the following general function notation:

$$f_r = f(f^{(1)}_{r-MLP}^{B-MLP}, f^{(22)}_{r-MLP}^{B-MLP}, W_{(1)}^{G-MLP})$$  \hspace{1cm} (11)

where $W^{G-MLP}$ is a weight matrix of G-MLP network:

$$W^{G-MLP} = \{w^G_1, \ldots, w^G_{N_{HB}}, w^G_o, b^G_1, \ldots, b^G_{N_{HB}}\}$$  \hspace{1cm} (12)

General symbol of hierarchical model is $\text{HIE}^{N_{HG}\text{(bmlp)}}_G - N^G_1 - \cdots - N^G_i - \cdots - N^G_L$ where $bmlp$ is the symbol for applied B-MLP network at first (basic) level, while $N^G_i$ is the number of neurons in the $i$-th G-MLP hidden layer.

Hierarchical model training is done in two steps. In the first step, training process of MLP networks of basic level is conducted in order to adjust parameters of weight matrix $W^{B-MLP}$ so that the total error $E(W^{B-MLP})$, between the desired outputs and the actual outputs from B-MLP network, is lower than the prescribed value $E_{cb}$ [3]. In the second step, training of generalized network is performed. During this training process, parameters of weight matrix $W^{G-MLP}$ have to be adjusted in order to make the total error $E(W^{G-MLP})$, between the desired outputs and the actual outputs from G-MLP network, lower than the prescribed value $E_{cg}$.

### 3 Modeling Example

In this section, the proposed hierarchical model is applied to calculate TM112 mode resonant frequencies in a cylindrical metallic cavity with circular cross-section and dimensions $a = 7$ cm and $h = 14.24$ cm (Fig.4). Cavity is loaded with two-layer dielectric placed at the cavity floor and represented by two planparallel homogeneous dielectric slabs.

In order to obtain the basic network with as higher accuracy as possible, training of various different $\text{MLP}^N_{HB} - N_1 - \cdots - N_l - \cdots - N_{HB}$ networks, where
$1 \leq N_{HB} \leq 3$ and $6 \leq N_l \leq 30$, is done using training set of 18081 uniformly distributed samples. Input parameters and their ranges are: $t_h = (0 \div 0.2)$, $\varepsilon_r = (2 \div 82)$ and $r_h = (0 \div 0.2)$. Quasi-Newton’s training algorithm with prescribed error value $E_{cb} = 10^{-4}$ is chosen.

![Cylindrical metallic cavity loaded with two-layer dielectric.](image)

Fig. 4. Cylindrical metallic cavity loaded with two-layer dielectric.

Testing of basic MLP networks is performed using testing set of 7680 samples. The testing results for several B-MLP models with the highest $r^{PPM}$ correlation coefficient are shown in Table 1. From this set of models, we have chosen MLP2-10-9 network as a basic network of hierarchical model because it had the highest $r^{PPM}$ correlation coefficient and the smallest test error. Scattering diagram for chosen B-MLP model is given in Fig. 5.

![Scattering diagram for MLP2-10-9 model.](image)

Fig. 5. Scattering diagram for MLP2-10-9 model.

Training of generalized network is performed by using training set of 10201 samples. In order to generate this training set, two MLP2-10-9 networks are used in the simulation process. For the first network the range of input parameters changes has been: $0 \leq t_{h1} \leq 0.2$, $\varepsilon_{r1} = 80$, and $r_{h1} = 0$, while input parameters have been changed in the range: $0 \leq t_{h2} \leq 0.2$, $\varepsilon_{r2} = 60$ and $0 \leq r_{h2} = t_{h1} \leq 0.2$ for the second
MLP network. In order to obtain the hierarchical model with as higher accuracy as possible, training of various different HIE_{HG(MLP2−10−9)} − N_1 − ··· − N_l − ··· − N_{HG} neural networks, where 1 ≤ N_{HG} ≤ 3 and 6 ≤ N_l ≤ 30, is done. Quasi-Newton training algorithm with prescribed error value E_{cb} = 10^{-4} is chosen.

Hierarchical model testing is done by using testing set of 10201 samples. As for the training procedure, two MLP2-10-9 networks are used in the simulation process for generation of this testing set. Range of input parameters changes for the first network has been: 0 ≤ t_{h1} ≤ 0.2, ε_{r1} = 50 and r_{h1} = 0, while for the second network input parameters have been changed in the range: 0 ≤ t_{h2} ≤ 0.2, ε_{r2} = 35 and 0 ≤ r_{h2} = t_{h1} ≤ 0.2. Testing results are given in Table 2. Based on test error analysis and rPPM correlation coefficient value, HIE2_{(MLP2−10−9)}22 − 22 model is adopted as final hierarchical model and its scattering diagram is shown in Fig.6.

For fixed relative permittivity of dielectric slabs: ε_{r1} = 50 and ε_{r2} = 35, three-dimensional (3D) presentation of the resonant frequency dependence versus cavity filling factors t_{h1} and t_{h2}, is obtained by using HIE2_{(MLP2−10−9)}22-22 model and compared with the results calculated by TRM. (Fig. 7). For 3D plot generated in 10000 points per area, HIE model takes less than 5 s (on Pentium IV 2.5 GHz-1 GB RAM hardware platform) and TRM takes about 20 hours to run, while both models produced similar results.
Fig. 7. Resonant frequency of TM_{112} mode versus cavity filling factors \( t_{h1} \) and \( t_{h2} \) obtained by using a) TRM and b) new hierarchical neural model.

4 Conclusion

In this paper, new hierarchical neural model of cylindrical metallic cavity loaded with multilayer dielectric is suggested. Model is based on superposition of separate influence of each dielectric slab to the cavity resonant frequency. Model accuracy and efficiency, illustrated on the example of two-layer dielectric, will be further investigated for other multilayer dielectric configurations.

References
