A BP Neural Network Realization in the Measurement of Material Permittivity

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***Abstract*—Effective complex permittivity measurements of materials are important in microwave engineering and microwave chemistry. The BP (Back Propagation) neural network computational module has been applied to microwave technology and becomes a useful tool recently. A neural network can be trained to learn the behavior of an effective complex permittivity of material under microwave irradiation in an experimental system. It can provide a fast and accurate result for the material permittivity. Thus, the on-line measurement has been realized. In this paper, a measurement system has been designed and the S-parameters are obtained by full-wave simulations to reconstruct the material permittivity. Moreover, several organic solvents have been measured. The relative errors of the reconstructed results for several organic solvents are less than 5% compared with reference data. The reconstructed results of the effective permittivities of solvents by means of the BP neural network are obtained quickly and accurately.**

***Index Terms*—BP (Back Propagation); Neural network; Effective permittivity; Measurement**

I. INTRODUCTION

Effective complex permittivity measurements of materials are important in microwave engineering, microwave material processing, microwave chemistry, and electrobiology[1-3]. In addition, microwave engineering requires precise knowledge of electromagnetic properties of materials at microwave frequencies since microwave communications are playing more and more important roles in military, industrial, and civilian life[4]. For these reasons, various microwave techniques have been introduced to characterize the electrical properties of materials. These methods can roughly be divided into resonant and non-resonant method [4]. Resonant methods have much better accuracy and sensitivity than nonresonant methods [5]. They are generally applied to preparation before measurements. In addition, for an analysis over a broad frequency band, a new measurement set-up (a cavity) must be made. On the other hand, non-resonant methods have relatively higher accuracy over a broad frequency band and necessitate less sample preparation compared to resonant methods [6]. Due to their relative simplicity, nonresonant coaxial transmission/reflection methods are presently the most widely used broadband measurement techniques [7].

Various non-resonant transmission-reflection methods have been proposed for electrical characterization of low-, medium, and high-loss materials [8-10]. Transmission measurements are convenient for gathering whole volume information [9], do not suffer much from surface roughness at high frequencies [8], and provide longitudinal averaging of variations in sample properties[9].

Especially, the reactants from a complicated mixture, which varies with time, an effective permittivity can be used to describe the molecular polarization of the mixture in the reaction [11]. The effective permittivity is expected to vary with respect to microwave frequency, temperature, and reaction time. However, in many cases, the effective permittivity of chemistry reaction is difficult to be measured on-line with traditional reconstruction algorithms. In a recent study, we proposed a measurement apparatus for relative complex permittivity (ε_r') and loss tangent ($tg\delta$) using transmission-only scattering (S-) parameter measurements by BP neural network reconstruction algorithms. Artificial neural network computational modules have gained recognition as an unconventional and useful tool for microwave technology recently [12]. Neural networks can be trained to learn the behavior of the effective complex permittivity of the material under microwave irradiation. It can provide a fast and accurate result of the measurement when it has learned.

In this paper, we present a simple and convenient reconstruction algorithm for determining the effective complex permittivity. Firstly, a measurement system is designed and the scattering (S-) parameter is calculated employing the frequency dependent finite difference time domain (FDTD) method. Secondly, we develop a BP nerve network and enough simulated materials are utilized to train the networks. Finally, the trained network is employed to reconstruct the effective complex permittivity of several organic solvents, and the results

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gained by the BP neural network agree well with the previous published data.

II. MEASURE MENTAL APPARATUS

In this section, the functionality of the BP algorithm is illustrated by examples. We use a new open ended coaxial probe to measure the scattering (S-) parameters contained in an iron can structure in this work. The measurement installation shows in figure1. For measuring the permittivity of liquid, solid or powder, many structures using coaxial line have been reported [13].

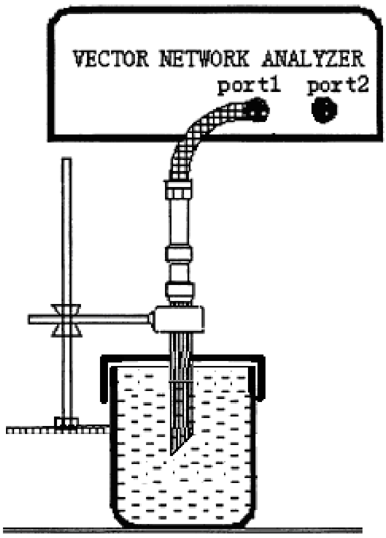

Figure 1. Measurement installation

However, in many cases, a change of the effective permittivity is too small to be observed by traditional methods. We propose an iron can to contain the material measured. The iron can structure is big enough, so that the scattering parameters which are used to reconstructed permittivity have been gained. Moreover, the coaxial probe has been designed the pointed-end for plug in powder easily shown in figure 2 and 3. To validate the performance of the coaxial structure, the experimental and computational results show that the coaxial probe is very sensitive to the change of the effective permittivity and they are fit well. In the process, the finite difference time domain (FDTD) method is employed because these materials to be studied are dispersive material and the simulation model as figure 4. Then, we develop multilayer perception (MLP) neural network based on back propagation (BP) arithmetic and use enough simulated materials as samples to train the networks.

III. BP ALGORITHM

Among all kinds of artificial neural network studied today, Back-propagation(BP) network, which depends on simple structure, strong operation-ability, imitation of every nonlinear relation between input and output, is widely applied in the fields such as function approximation, pattern identification, classification and data compress, image process, system control and so on[14-15]. In fact, it is to modify weight coefficient, according to negative grads direction of error function, to make error decrease.

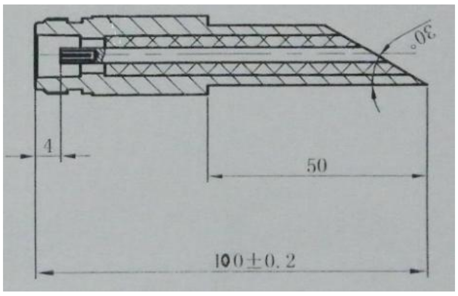

Figure 2. Structure of the coaxial probe

Figure 3. Coaxial probe

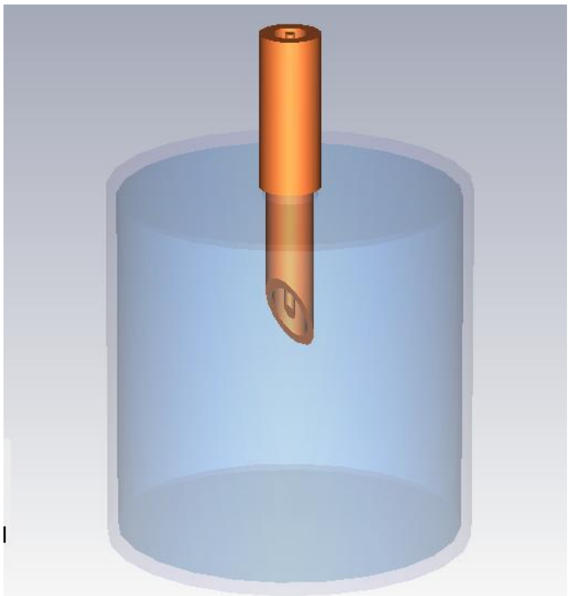

Figure 4. Simulation model

A. *Diagram of BP Algorithm*

BP neural network is a kind of typical forward network, composed of input layer, hidden layer and output layer.

Full interconnect from is among the layers. And disconnect form between two neural units of the same layer. BP network transmits directly and information transmission is bidirectional. In this paper, BP neural network has been used to reconstruct the effective complex permittivity of material measured by scattering parameter (|S11|, $\varphi_{S_{11}}$) and Its diagram is shown as Figure 5.

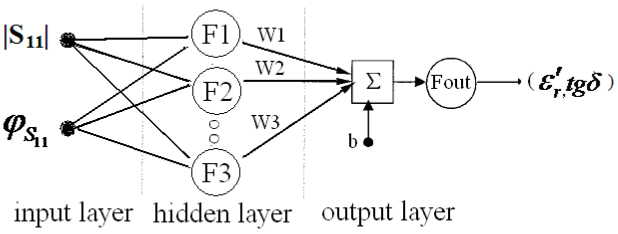

Figure 5. The structure of the BP

1.Information positive transmission

Input information, from input layer and processed by hidden layer, is transmitted to output layer.

Input layer: input value is every branch value of the example, output value of input layer is equal to the branch value of the example generally.

Hidden layer: hidden layer has single layer or multilayer.

To node j, its input value x_j is the sum, adding the output value y_i of every node in the former layer:

$$x_j = \sum_i w_{ij} y_i \tag{1}$$

Its output value is:

$$y_j = f_s(x_j) \tag{2}$$

$f_s(*)$ is excitation function, using sigmoid function generally:

$$f_s(*) = \frac{1}{1+e^{-(x_j-\theta_j)}} \tag{3}$$

θ_j is the threshold value of node j, and $f'(x) = f(x)\left[1-f(x)\right]$.

Output layer: to node k, its input x_k and output y_k are respectively:

$$x_k = \sum w_{jk} y_j \tag{4}$$

$$y_k = f(x_k) \tag{5}$$

Linear functions are usually used in output layers.

2. Error back propagation [14]

When the real output value from neural network is not equal to the expecting value, error e will be gotten. Use the negative gradient descent way to make connecting weigh return following the former connecting access and have error function decrease by modifying the weight of each layer. Among them, error function generally chooses the LMS error estimator to calculate error.

Suppose the real output from the network is y_{pk} and expecting output is t_{pk}, so mean-square error function E_p is:

$$E_p = \frac{1}{2}\sum_k \left(t_{pk} - y_{pk}\right)^2 \tag{6}$$

Among that, k denotes the k unit of the output. P denotes the p input example.

To all the learning example, the system mean-error is:

$$E = \frac{1}{2P}\sum_P \sum_k \left(t_{pk} - y_{pk}\right)^2 \tag{7}$$

Using the steepest descent back propagation to modify weigh:

Weigh regulation between output layer and hidden layer:

$$w_{jk}(t+1) = w_{jk}(t) + \Delta w_{jk} \tag{8}$$

among that,

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} \tag{9}$$

$\eta \in (0,1)$ is learning rate.

Have the Eq.(6) into the Eq.(9):

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta \bullet \frac{\partial E}{\partial y_k} \bullet \frac{\partial y_k}{\partial w_{jk}} \tag{10}$$

$$\Delta w_{jk} = \eta \bullet (t_k - y_k) \bullet y_k \bullet (1-y_k) \bullet y_j \tag{11}$$

among them:

$$\delta_k = (t_k - y_k) \bullet y_k \bullet (1-y_k) \tag{12}$$

Weigh regulation between the input layer and hidden layer:

$$w_{ij}(i+1) = w_{ij}(t) + \Delta w_{ij} \tag{13}$$

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = \eta \bullet \delta_j \bullet x_i \tag{14}$$

in the Eq.(14)

$$\delta_j = \sum_k \delta_k w_{jk} y_j (1-y_j) y_j \tag{15}$$

B. Fundamental Principle of BP Algorithm[16]

A neural network is created with one or more levels of hidden nodes to model a system. There are multiple connections from the inputs to the nodes on the hidden layers to the output, which all have a weight and error term, which are adjusted through the training process. Since there is a tremendous amount of interconnectedness between all nodes from the inputs to the output, a neural network can expose relationships that were previously unsuspected before the analysis. During the training process, the network assigns weights to the nodes to achieve the best relationship between the training input and output values, The neural network runs through the process many times adjusting weights to minimize the error. The number of hidden nodes was initially chosen by the Baum-Haussler heuristic, although some experiments were done with modified values.[17] The weights were initialized with random values from the range[-0.3,0.3] and the learning rate was set at 0.3.(For more discussion of these terms, see [18].) Once trained, the network has a model with the weights that provided the best results to calculate the estimate for a part that was not in the training data set. A Back-propagation (BP) neural network creates an optimal model that is general in nature and produces a small mean square error for data that was not in the training set[19].

Input sample is transferred form input layer to output layer via one or more hidden layers. If there exists error between real output and desired output, Error Back Propagation will begin to operate. Above-mentioned is signal forward propagation. Meanwhile, output error will be propagated reversely from hidden layer to input layer, which named error back propagation. Error signal of every layer will have been obtained and become a basis to correct weight-value of every neuron.

Signal forward propagation and error back propagation are running go round and begin again until network output error will up to the standard.

C. reconstruction of permittivity for material by BP network

The figure 6 shows the process to reconstruct the permittivity for material by BP net work

Compared with other conventional reconstruction algorithm, BP neural network has some advantages: on the one hand, the result can be gained very quickly once the network has been trained, because the samples have been produced by the finite difference time domain (FDTD) method before trained. The network has been trained by samples before measurement and saved, then the test data gotten from measurement. Once the test data has been input in the network trained, result can be gained in several seconds. The test data, on the other hand, can be processed parallel. Many reconstruct results can be gained at one time. So the on-line measurement has realized by using BP neural network.

D. Construction of the Sample Space[18]

In this section we describe the creation of the sample space, and the training of the network. How information from the preconditioned system can be used to increase reconstruction accuracy.

The neural network algorithm may also be addressed in context of training data manipulation [8]. For example, in [9], a learning strategy is implemented through the selection of most informative training samples. Given enough data, an BP neural network will reconstruct the permittivities of materials and produce a more accurate result. The accuracy for reconstruction of permittivity depend on the amount of data available in this loss dielectric materials

1.The produce of sample data

Before constituting the model the primary question is the production of samples. On the one hand, the characteristic of network should be considered; on the

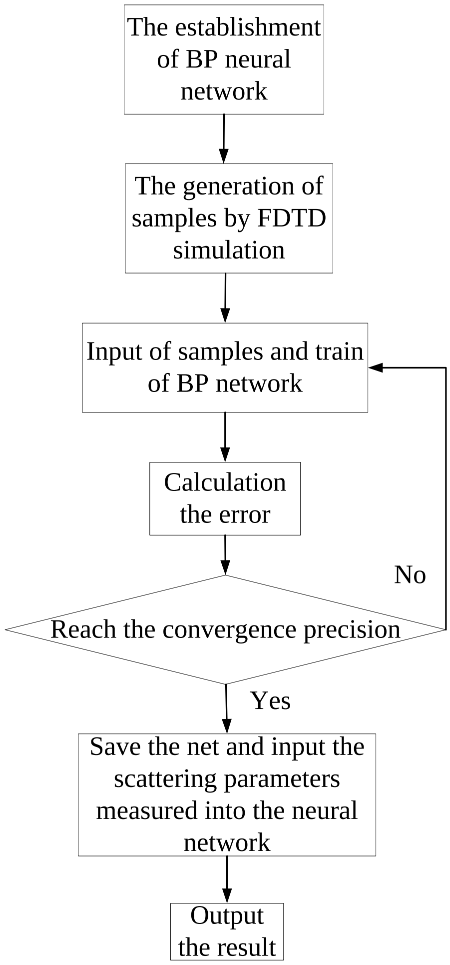

Figure 6. The flow chart of reconstruction permittivity by BP

other hand, the sample data must do their best to reflect the intrinsic rule of permittivities. The learning strategy is implemented through the selection of most informative training samples[9]. The sensitivity analysis algorithm defines pattern informativeness as the sensitivity of the neural network output to perturbations in the input value of that pattern.[20] In[20], the output sensitivity vector is defined as (17), That is,

$$\Phi^{(p)} = \left\| \vec{S}_o^{(P)} \right\|_\infty = \max_{k=1,\cdots,K} \left\{ \left| S_{o,k}^{(P)} \right| \right\} \tag{16}$$

Where $\Phi^{(p)}$ is the informativeness of pattern p, $\vec{S}_o^{(P)}$ is the output sensitivity vector for pattern p, and $S_{o,k}^{(p)}$ refers to the sensitivity of a single output unit o_k to changes in the input vector $\vec{z}$; K is the total number of output units. The output sensitivity vector is defined as

$$\vec{S}_o^{(p)} = \left\| S_{oz}^{(p)} \right\|_2 \tag{17}$$

Where $S_{oz}^{(p)}$ is the output-input layer sensitivity matrix. Each element $S_{oz,ki}^{(p)}$ of the sensitivity matrix is defined as (assuming differentiable activation functions)

$$S_{oz,ki}^{(p)} = \frac{\partial o_k}{\partial z_i^{(p)}} \tag{18}$$

Each element k of $\vec{S}_o^{(p)}$ is then computed as

$$S_{o,K}^{(p)} = \sqrt{\sum_{i=1}^{I} \left(S_{oz}^{(p)} \right)^2} \tag{19}$$

In this paper, The FDTD is applied to simulate the |S11| and $\varphi_{S_{11}}$, using the real and the imaginary part of materials as input parameters. at different permittivities of materials. For example, figure 7 shows the phase variation of S- parameters due to the change in real part of permittivities. The slope for the curve which expresses the sensitivity of the output changes from small to big with the input data increasing. The slope is bigger at the low permittivity materials areas than the high permittivity materials areas, and the samples in low permittivity materials areas are more informative, the more samples have been selected in training neural networks. In addition, the low permittivity materials have bigger relative errors with the same absolute reconstruction errors. The more samples have been selected to improve the accuracy of reconstruction by BP neural network so that the relative errors of measurement for the materials permittivities are less than 5%.

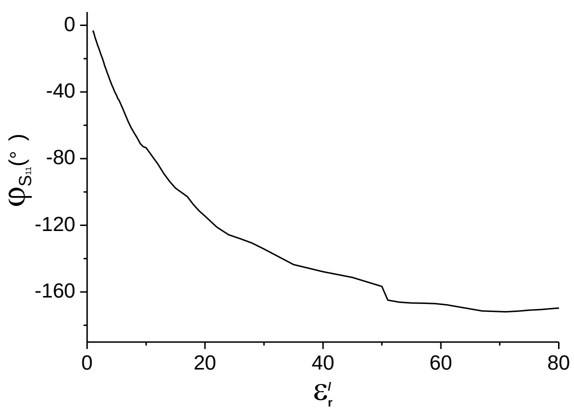

Figure 7. Phase variation of S-parameters due to the change in real part of permittivities at 2.45GHz.

E. The training of the BP neural network[nn7]

The BP neural network training comprises the following tasks: (ⅰ) select the proper training set, (ⅱ) find a suitable network architecture and (ⅲ) determine the appropriate values of characteristic parameters such as the learning rate and monentum term.

The learning rate coefficient and the momentum term are two user defind BP parameters that effect the learning procedure of BP neural network. The training is sensitive to the choice of these parameters. The learning rate coefficient, employed during the adjustment of weights changes; hence large steps are taken toward the global minimum of error level, while smaller learning cofficients increase the number of steps taken to reach the desired error level. If an error curve shows a downward trend but with poor convergence rate the learning rate coefficient is likely to be too high. Although these learning rate coefficient are usually taken to be constant for the whole net, local learning rate coefficients for each individual layer or unit may be applied as well.

The basic BP neural network configuration employed in this study is selected to have one hidden layer, An improtant factor governing the success of the learning procedure of neural network architectkure is the selectiong of the training set. A sufficient number of input data properly distributed in the design space together with the output data resulting from complete structural analyses are needed for the BP algorithm in order to provide satisfactory results. Overloading the network with unnecessary similar information results to over training without increasing the accuracy of the predictions. A few tens of limit elasto-plastic analyses have been found sufficient for the example considered to produce a satisfactory training of the BP neural network.

In this work a fully connected network is used. The number of conventional step-by-step limit analysis calculations performed in order to built up the proper data for the training set is in the range of thirty[nn8]. This selection is based on the requirement that the full range of possible results should be represented in the training procedure. For the application of the BP neural network simulation and for the selection of the suitable training pairs, the sample space for each random variable is divided into unequally spaced distances. The samples in low permittivity materials areas are more informative, the more samples have been selected in training neural networks. The cectral points within the intervals are used as inputs for the limit satae analyses.

F. BP neural network box in MATLAB

Software MATLAB7.0 supply a neural network toolbox(Neural Network Toolbox, for short, NNbox). Next, aiming at BP network establishment and training, I will introduce how to program with these function, based on Nnbox-relation function.

MATLAB neural network toolbox supplies professional function new ff( )[nn10] for neural network establishment. The grammar of it is as follows:

net=newff(Xr,[S1 S2…SN1],{TF1 TF2 …TFN1}, BTF, BLF, PF) （20）

In the Eq.(20) above, Xr is a input vector, which has 2 lines that denotes the minimum and the maxium of the input vector respectively. [S1 S2 … SN1] express, in turn, the unit number of the hidden layers and output layers in BP network; {TF1 TF2… TFN1} represent respectively the functions in the hidden layer and the output layer. The function, such as tansig, logsig and purelin and so on, can be used and “tansig” is default; BTF, which expresses back train function in network, is character string variable and “trainlm” is default; BLF, which represents back weigh learning function, is a character string variable and “learndm” is default ; PF, which expresses performance function concluding mae （calculating network average absolute error）, mser(calculating mean-square error), msereg (calculating mean-square error and the weighting of weigh or threshold value) and sse (calculating network mean-square sum) is a character string variable calculating network output error to provide criterion for training, which choose “mse” as default; net is new creating BP neural network. BTF, BLF and PF will be set in terms of requirement, of omitted.

After defining network structure, newff will automatically transfer the function “init” with drfault paramter to initialize each weigh and threshold value in network, which will create a trainable for feedforward network with “net’as the return value.

Due to the compress effect nonlinear transfer function gives the output, the output layer usually adopts linear transfer function to keep the output range.

IV. MEASUREMENT RESULTS

The permittivity of material can be gained when the scattering parameters measured have been put in the trained BP network. So the trained network can use the scattering parameter to measure the effective complex permittivity of materials quickly. Table Ⅰ shows the reconstructed results of several organic solvents and The relative errors of the reconstructed results for several organic solvents are less than 5% compared with reference data. TableⅡshows the reconstructed results of the permittivities of NaCl powder at different moisture contents. The accurate restructured results have been gained by BP network.

TABLE I Effective permittivities of material at 2.45GHz

Material name	real part of complex permittivity		
	Measurement result	Reference[21] result	relative errors （%）
DMSO	46.89	48.9	-4.1
Methanol	25.91	24.97	3.8
Formic acid	6.839	7.135	- 4.2
ethanol	8.68	8.939	-2.9

Material name	Loss tangent		
	Measurement result	Reference[21] Result	relative errors （%）
DMSO	0.393	0.409	-3.9
Methanol	0.561	0.582	- 3.6
Formic acid	0.242	0.236	2.5
ethanol	0.880	0.849	3.7

TABLE II Effective permittivities of NaCl powder with different moisture content at 2.45GHz

moisture content (%) / complex permittivity	0.5	1	1.5	2	2.5
Real part	3.12	3.38	3.72	3.99	4.37
loss tangent	0.10	0.13	0.18	0.23	0.28

moisture content (%) / complex permittivity	3	3.5	4	4.5	5
Real part	4.56	4.62	4.66	4.95	5.20
loss tangent	0.31	0.37	0.38	0.43	0.49

V. CONCLUSIONS

In this paper, we have designed an open-ended coaxial probe to measure the scattering parameters, and the techniques of BP reconstruction have been applied to the measurement of the complex permittivity. The BP network is a simple, fast and convenient method to reconstruct the permittivity of materials. The measured results show the BP neural network can be applied to microwave measurements and work well.

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