The paper discusses characteristics of a new modeling-based technique for determining dielectric properties of materials. Complex permittivity is found with an optimization algorithm designed to match complex S-parameters obtained from measurements and from 3D FDTD simulation. The method is developed on a two-port (waveguide-type) fixture and deals with complex reflection and transmission characteristics at the frequency of interest. A computational part is constructed as an inverse-RBF-network-based procedure that reconstructs dielectric constant and the loss factor of the sample from the FDTD modeling data sets and the measured reflection and transmission coefficients. As such, it is applicable to samples and cavities of arbitrary configurations provided that the geometry of the experimental setup is adequately represented by the FDTD model. The practical implementation of the method considered in this paper is a section of a WR975 waveguide containing a sample of a liquid in a cylindrical cutout of a rectangular Teflon cup. The method is run in two stages and employs two databases – first, built for a sparse grid on the complex permittivity plane, in order to locate a domain with an anticipated solution and, second, made as a denser grid covering the determined domain, for finding an exact location of the complex permittivity point. Numerical tests demonstrate that the computational part of the method is highly accurate even when the modeling data is represented by relatively small data sets. When working with reflection and transmission coefficients measured in an actual experimental fixture and reconstructing a low dielectric constant and the loss factor, the technique may be less accurate. It is shown that the employed neural network is capable of finding complex permittivity of the sample when experimental data on the reflection and transmission coefficients are numerically dispersive (noise-contaminated). A special modeling test is proposed for validating the results; it confirms that the values of complex permittivity for several liquids (including salt water, acetone and three types of alcohol) at 915 MHz are reconstructed with satisfactory accuracy.

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INTRODUCTION

Nowadays, with the remarkable progress of computational resources, computer-aided design (CAD) has become a valuable component in developing systems of microwave power engineering. Knowledge of complex permittivity ($\varepsilon = \varepsilon' - i\varepsilon''$) of materials involved in an application is critical for creating an adequate model and thus for successful system design. However, the dielectric constant $\varepsilon'$ and...
The present paper discusses the outcome of further practice-oriented development of this modeling-based technique. In particular, we describe its implementation in a two-port (WR975-based) fixture, outline corresponding neural network operations along with their realization in a MATLAB code, and demonstrate an advantageous capability of the employed inverse ANN to reconstruct complex permittivity from experimental $S$-parameters which may be noise-contaminated (i.e., numerically dispersive). High accuracy of the method is illustrated by detailed numerical tests and by finding complex permittivity of tap water determined by other techniques. To make practical exploitation of the method convenient and flexible and to reduce its computational cost, we propose to run it in accordance with a particular two-stage operational strategy. A special modeling-based validation technique is introduced in order to facilitate routine operations of the method in an industrial environment; this technique is used to ensure a sufficient accuracy of $\varepsilon'$ and $\varepsilon''$ reconstructed for several liquids at 915 MHz.

METHOD

**Experimental Setup**

While initially the ANN-assisted reconstruction techniques [Olmi et al., 2002; Eves et al., 2004a] employed resonant-type systems, the experimental part of the method described in this paper is implemented with a two-port waveguide-type system introduced in [Eves et al., 2004b; Yakovlev et al., 2005] and shown in Figure 1. The fixture is set for measuring the magnitude and phase of the reflection and transmission coefficients (or, in terms of $S$-parameters, $|S_{11}|$, $\angle S_{11}$, $|S_{21}|$, $\angle S_{21}$) at the frequency of interest $f_0$. A two-port approach allows us to work with a set of $S$-parameters at one frequency instead of several points of an $|S_{11}|$ frequency response in the one-port scheme exploited by Olmi et al.
[2002] and Eves et al. [2004a]. This expands the capabilities and accuracy of the method: if the measured material turns out to be dispersive, the ability of the associated FDTD solver to take this into account is not required. While two-port techniques are well-established in engineering practice for determining dielectric properties of materials (see, e.g., [Baker-Jarvis et al., 1990]) and known for their use in modeling-based reconstruction techniques [Pitarch et al., 2006], exploitation of a two-port concept in the ANN-assisted methods may be particularly advantageous since it brings more information to the associated neural network and thus helps improve mapping from the $S$-parameter space to the complex permittivity space.

A test sample is supposed to be placed somewhere inside the fixture. The experimental setup described here is particularly convenient for working with liquids or soft substances which are put in a cylindrical cutout of the rectangular Teflon block (Figure 1(b)). The “vertical” orientation of the waveguide fixture is introduced in order to arrange for the air-sample media interface to be parallel to the electric field and thus to make the fixture’s parameters not sensitive to an occasional uncertainty in the interface’s location – the phenomenon noticed earlier by Eves et al. [2004a]. The fixture is connected with the HP 8510C Network Analyzer through the standard waveguide-to-coax transitions.

**Network Operations**

The inverse radial basis function (RBF) network used in this work is shown in Figure 2. For network training and testing, we use data generated in the modeling stage of the method; the latter is powered by the 3D conformal FDTD method. The input layer receives the values of $\varepsilon'$ and $\varepsilon''$ for which four $S$-parameters associated with the output layer are computed. The output of the networks is given by the formula

$$S_I = \sum_{j=0}^{N} w_{ij}^{3} \sigma \left( \sum_{i=0}^{2} w_{ij}^{2} \varepsilon_i \right)$$

(1)

where $l = 1, \ldots, 4$, $S_I$ is an element of the vector

$$S = \begin{bmatrix} S_1 & \ldots & S_4 \end{bmatrix}^T = \begin{bmatrix} \text{Re}(S_{11}) & \text{Im}(S_{11}) & \text{Re}(S_{21}) & \text{Im}(S_{21}) \end{bmatrix}^T$$

(2)
and $w^{2|3}_{pq}$ represents the network weights of the links between the $q$th neuron in the 1st or 2nd layer and the $p$th neuron in the 2nd or 3rd layer. For the neurons in the hidden layer, the activation function is either the local Gaussian function $\sigma(\gamma) = e^{-\gamma^2}$, or the global cubic function; for the neurons in the output layer, the activation function is linear.

The training data are pairs of $(\varepsilon_k, \Sigma_k)$, where $\Sigma_k$ is the desired outputs of the network for inputs $\varepsilon_k$ (i.e., the values of $S$-parameters simulated for given $\varepsilon_k$). Computation of error is preceded by minimization of the function

$$G_k = \|S_k(\varepsilon_k, w) - \Sigma_k\|^2$$

(3)

where $k = 1, \ldots, P, l = 1, \ldots, 4$, $S_k(\varepsilon_k, w)$ is the ANN output for input $\varepsilon_k$, and $P$ is the number of training vectors. The solution to this minimization problem is a set of approximated complex permittivity values. The network error is determined from:

$$e_{S_l} = \frac{1}{2} \sum_{k=1}^{P} \left[ \min(G_k) - \Sigma_k \right]^2$$

(4)

Two training techniques, namely backpropagation and the second-order gradient-based algorithm are implemented with the use of the gradient method (iterations from 1 to 200) and the Levenberg-Marquardt method (iterations beyond 200), respectively. When the network is sufficiently trained, it is supplied with the values of measured complex $S$-parameters and determines the $\varepsilon'$ and $\varepsilon''$ of the sample.

**Computational Procedure**

Since electromagnetic characteristics of the fixture depend on complex permittivity of the material contained in it, the related FDTD model (and, in particular, its mesh) should be

built in accordance with the values of $\varepsilon'$ and $\varepsilon''$. This means that, when generating data for training and testing the network, it would not be feasible to employ the model with the same parameters for computation of the vector $S$ on the entire complex permittivity plane. To this end, we work with a special two-step procedure allowing us to roughly estimate the position of the unknown $(\varepsilon', \varepsilon'')$-point and then focus on the neighborhood of this position in order to find its exact location.

At the first stage, the entire domain of physically possible complex permittivity values is associated with a relatively sparse lattice of the points of the primary database (DB); we work with its structure shown in Figure 3. Here, the employed FDTD model is built with the cells whose size within the sample is determined by the largest value of its dielectric constant – in this example, by $\varepsilon' \sim 85$. The DB size is intentionally small, so with the ANN operations described above, we reconstruct the $(\varepsilon', \varepsilon'')$-pair indicating in which domain (from I to XII) the actual point is located. If it is, e.g., in domain IV, then, at the second stage, we form the secondary DB surrounding the expected position of the point we are looking for; in the FDTD model, the smallest cell size becomes larger as it is conditioned now by the largest value of $\varepsilon'$ in the secondary DB – in the considered example, by $\varepsilon' \sim 45$. This approach substantially reduces the computational cost of our method since it does not require too much analysis with the
smallest cells on the entire $\varepsilon$-plane.

The measures taken to enhance the generalization of the network and to make it better prepared for handling data taken from the related measurements (which may be noise-contaminated) include the optimization of the RBF radius [Murphy and Yakovlev, 2006], the improvement of smoothness of data with the use of ridge regression [Orr, 1996] and an adjustment of the FDTD model in accordance with the calibration of the experimental setup. The latter means that in the model the distance between the input and output reference planes of the virtual ports can be set up prior to the generation of the database following the measurement of $\angle S_{21}$ in the empty waveguide.

The computational part of our method is implemented as a MATLAB code using several functions of the MATLAB Optimization Toolbox. The code is designed as two separate pieces of software: Database Maker (DM) and Permittivity Reconstructor (PR); their MATLAB-based graphical user interfaces (GUI) are shown in Figure 4. Data for training and testing are generated by a model built with the 3D conformal FDTD simulator QuickWave-3D (QW-3D) [QuickWave-3D, 1996-2007] which precisely reproduces the geometry of the experimental fixture.

The functionality of the developed computational procedure can be described by referring to the GUIs (Figure 4). DM governing operations of QW-3D is given the name of the related model (here, Fci_dc552.pro), the number of FDTD time-steps required to reach steady state (e.g., 5000), the operating frequency (915 MHz) and the parameters of the required secondary DB: its boundaries [$\varepsilon' \in (18, 38)$ and $\varepsilon'' \in (0.5, 20)$] and the numbers of points along the $\varepsilon'$- and $\varepsilon''$-axes (10 and 10). By pressing the Run button, we have DM make a DB and structure it as a single *.mat file with the name containing the information about the boundaries of the DB and the number of points in it (Fci_dc552_18to38a0o5to20_100.mat in this example).

This name is then chosen from the pop-up field on the top of the PR interface. PR reads the * .mat file and trains the network (the Train button) with the chosen RBF function (Gaussian or cubic) and optional optimization of the RBF’s radius, and informs the user on the testing results: the scalar-optimized radius, regularization parameter produced by ridge regression, mean square error of training and CPU time elapsed for training. By pressing the Display

![Figure 3](image-url)

**Figure 3.** 12 domains for identification of anticipated location of the sought point on the $\varepsilon$-plane (a) and the structure of the primary DB used in the described tests (b); (o) and (×) denote training and testing points respectively.
Accuracy button we get a visual illustration of the accuracy of the network operations by displaying the complex permittivity plane with the testing points and the network responses. The Testing Error vs. Radii button plots the network testing error versus several values of the RBF’s radius. The best radius/radii are not necessarily a unique solution, so this plot verifies that the chosen radius/radii is/are reasonable. We can also plot the training points along with corresponding circles around them with the best radii found (the Show Radii button). Since the radius is the basic range of “influence” each RBF center has, this plot shows whether the radii are reasonable for the data. If the results do not appear satisfactory, it is possible to retrain the network with a lower error bound (e.g., 3%) by typing a new number in the corresponding field and pressing the Re-Train button. By this, the network is retrained with all the testing points that have an error of more than 3% turned into training points. Finally, the user enters the measured values of Re($S_{11}$), ..., Im($S_{21}$) in the respective fields and presses the Get Permittivity button. PR then determines the $\epsilon'$ and $\epsilon''$ of the considered sample and shows them in the Eps' and Eps” fields. PR also displays some text messages regarding the conducted network operations in the field on the bottom of the menu. In the considered example, PR informs the user that there is a 0.96% relative difference between the measured/inputted values of $S$-parameters and the network response.

Testing

Systematic numerical testing of the network performance has been carried out with the model of the experimental WR975-based 457 mm length fixture containing the rectangular (70×70×50 mm) block made of an unspecified Teflon-based polymer and having a cylindrical cutout (radius 25 mm, height 40 mm) (Figure 5). The model which precisely reproduces

Figure 4. General views of the DM (a) and PR windows (b).
the geometry of the actual device contains, depending on the dielectric constant of the sample, from 60,000 to 265,000 cells and uses 6 to 25 MB of RAM respectively. The tests show that the computational scheme implemented in this technique is highly accurate. For example, using the secondary DBs of 36 to 64 points for each sub-domain in Figure 3(a), the dielectric constant and the loss factor are determined with less than 1% error on most of the $\varepsilon$-plane; typical level curves illustrating the results of these tests are shown in Figure 6.

We have also performed two special tests to illustrate the operations of the method in its entirety, i.e., with the use of $S$-parameters measured in the actual experimental fixture. The first one was concerned with tap water – one of the practical materials whose dielectric properties at 915 MHz are relatively well studied. The values of $\varepsilon'$ and $\varepsilon''$ reconstructed by the present method are given in Table 1 along with the ones obtained by two other techniques. It can be seen that the results are in excellent agreement: the percent difference does not exceed 0.12% for $\varepsilon'$ and 3.0% for $\varepsilon''$. Although the output of both ANN methods is based on the experiments with water taken from the tap in the same location (Nashua, NH), the measurements were carried out in different seasons and the temperature of water was then slightly different; these factors might account for the minor difference in the values of $\varepsilon''$.

Another test aiming to check the performance of the technique in determining low-valued complex permittivity and in handling samples of complex configuration was carried out with an empty cup (Figure 1(b)) as a sample. Comparing the values of Teflon’s dielectric constant and the loss factor measured by different authors at 700 MHz [Givot and Krupka, 2004], 2.45 GHz [Arai et al., 1995], 2.78 GHz [Santra and Limaye, 2005] and in the range from 8.5 to 12.0 GHz [Deshpande et al., 1997; Krupka et al., 1998; Terhzaz et al., 2007; Easton et al., 2007], one may conclude that these characteristics are practically frequency-independent. In accordance with the above mentioned papers, for Teflon and Teflon-based polymers, dielectric constant and the loss factor vary in the intervals $2.0 \leq \varepsilon' \leq 2.58$ and $0.0005 \leq \varepsilon'' \leq 0.06$. The point $(\varepsilon', \varepsilon'') = (2.5, 0.01)$ reconstructed by our technique for the cup at 915 MHz lies within this domain; however, we admit that in this test the accuracy of reconstruction may be deteriorated. The points in the secondary DB for the domain of the low $\varepsilon'$ and $\varepsilon''$ are characterized by fairly insignificant variations of $S$-parameters, and this can be a reason for less efficient network learning and thus a decreased technique’s resolution. We attribute the varying accuracy of our reconstruction to the aforementioned issues in the practical implementation of the method rather than to only principal disadvantages. On the other hand, this test proves applicability of the method to the samples of complex configurations.

Figure 5. 3D general view of representation of the fixture in the FDTD model (a) and a typical non-uniform mesh in the xy-plane (b).
Table 1. Testing the Method with Tap Water at 915 MHz.

<table>
<thead>
<tr>
<th>Technique</th>
<th>$\varepsilon'$</th>
<th>$\varepsilon''$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polynomial model by Eves and Yakovlev [2002]</td>
<td>80.5</td>
<td>4.30</td>
</tr>
<tr>
<td>Method by Eves et al. [2004a]: 1 port, direct MLP ANN</td>
<td>80.6</td>
<td>4.25</td>
</tr>
<tr>
<td>Method of this paper: 2-ports, inverse RBF ANN</td>
<td>80.5</td>
<td>4.17</td>
</tr>
</tbody>
</table>

Figure 6. Accuracy of reconstruction of dielectric constant (a, c) and the loss factor (b, d) – numerical tests with 36- (a, b) and 64-point databases (c, d) on the $\varepsilon$-plane.
METHOD IN OPERATION AND RESULTS

Reconstructed Permittivity and Validation Technique

Table 2 contains the values of complex permittivity reconstructed by the present technique for 6 sample liquids. The primary DB (130 points) was generated once for all samples in accordance with the lattice shown in Figure 3. The secondary DBs for DA and EGW (both 63 points) were built around the boundary of domains I and IV (Figure 7(a)) and around domain VII (Figure 7(b)) respectively. For AC and SW, the estimated positions of the \((\varepsilon', \varepsilon'')\)-points turned out to be out of the domain covered by the primary DB; in these cases, we looked for appropriate adjacent areas. The secondary DBs, which were found suitable for EGW and AC (20 and 63 points respectively), are shown in Figure 7(c,d). Quality of network training by two 63-point DBs is illustrated in Figure 8 by the outputs of the PR’s Display Accuracy function for AC and SW. The obtained distributions of the testing points and the network responses confirm that the computational part of our method is very efficient: the network demonstrates excellent learning from relatively small data sets.

Generally, the conventional techniques of determination of complex permittivity are known to be different in accuracy, and they are usually associated with precise and laborious preparation of the samples to comply with strict dimensional tolerance requirements. Moreover, the results produced by a particular technique may vary depending on a variety of experimental conditions. Although our modeling-based ANN-backed technique is supported by elementary measurements of \(S\)-parameters, reliability of reconstructed \(\varepsilon'\) and \(\varepsilon''\) is still a key factor in routine practical exploitation of this method. Validation of the results obtained for “new” materials (i.e. the ones whose complex permittivity has never been determined before) by other highly reliable methods may be either difficult or impossible. Therefore, we introduce here a special modeling-based validation procedure checking the reconstructed values of \(\varepsilon'\) and \(\varepsilon''\) without alternative methods and thus making the described technique self-sufficient in its operations in a real-life industrial environment.

To validate the results, we run the FDTD model of the experimental fixture with input data of the reconstructed complex permittivity, but for an alternative geometry – for example, for the Teflon cup half-filled with liquid. The real and imaginary parts of \(S\)-parameters corresponding to this case are simulated and measured; in Table 3, we present the absolute values of \(\text{Re}(\mathcal{S}_{11})\), \(\text{Im}(\mathcal{S}_{21})\) for the materials whose reconstructed \(\varepsilon'\) and \(\varepsilon''\) are given in Table 1. In the absence of any preliminary knowledge on the dielectric constant and the loss factor of the tested material, this comparison may provide clear evidence of how close the reconstructed complex permittivity is to the unknown “true”

### Table 2. Reconstructed Complex Permittivity of Tested Liquids at 915 MHz

<table>
<thead>
<tr>
<th>Sample</th>
<th>Material</th>
<th>Temp., Cº</th>
<th>(\varepsilon')</th>
<th>(\varepsilon'')</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Acetone</td>
<td>22.5</td>
<td>20.1</td>
<td>0.44</td>
</tr>
<tr>
<td>DA</td>
<td>Denatured alcohol</td>
<td>21.0</td>
<td>24.7</td>
<td>10.3</td>
</tr>
<tr>
<td>ERA</td>
<td>Ethyl rubbing alcohol 70%</td>
<td>21.5</td>
<td>34.0</td>
<td>9.6</td>
</tr>
<tr>
<td>IRA</td>
<td>Isopropyl rubbing alcohol 70%</td>
<td>23.4</td>
<td>28.5</td>
<td>9.1</td>
</tr>
<tr>
<td>EGW</td>
<td>Ethylene glycol (68%) + water (32%)</td>
<td>22.7</td>
<td>60.8</td>
<td>13.1</td>
</tr>
<tr>
<td>SW</td>
<td>Salt water (3.88% NaCl by weight)</td>
<td>22.5</td>
<td>66.0</td>
<td>139.0</td>
</tr>
</tbody>
</table>
Figure 7. 12 domains of the secondary DBs used in the described tests for DA (a), EGW (b), AC (c), and SW (d).

Figure 8. ANN responses (×) to the testing points (○) for EGW (a) and DA (b).
one. For all the liquids studied in this paper, the measured and simulated values of $S$-parameters in the half-filled geometry differ by no more than 0.013; this suggests that our method reconstructs complex permittivity with an accuracy sufficient for most of CAD purposes.

In practice, it is convenient to measure $S$-parameters of the fixture with an alternative geometry during the same experimental session that is held for measuring reflection and transmission characteristics of the original scenario. Validation of the reconstructed $\varepsilon'$ and $\varepsilon''$ is then reduced to a single run of a slightly modified model with these values assigned to the tested material.

In the above examples of complex permittivity reconstruction, the computational cost of the method is completely determined by the time spent on DB generation. As such, similar to the technique by Olmi et al. [2002], our method can be used in real-time monitoring of $\varepsilon'$ and $\varepsilon''$ assuming that the FDTD computation is performed during the preceding off-line phase of the method’s operation.

### Table 3. Validation of the Results in Table 2 – Scenario with Half a Sample.

<table>
<thead>
<tr>
<th>Sample</th>
<th>$S$-Parameter</th>
<th>Re($S_{11}$)</th>
<th>Im($S_{21}$)</th>
<th>Re($S_{21}$)</th>
<th>Im($S_{21}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Measured</td>
<td>-0.015</td>
<td>-0.035</td>
<td>0.946</td>
<td>-0.321</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.013</td>
<td>-0.038</td>
<td>0.945</td>
<td>-0.322</td>
</tr>
<tr>
<td>DA</td>
<td>Measured</td>
<td>-0.023</td>
<td>-0.038</td>
<td>0.935</td>
<td>-0.323</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.023</td>
<td>-0.039</td>
<td>0.934</td>
<td>-0.323</td>
</tr>
<tr>
<td>ERA</td>
<td>Measured</td>
<td>-0.024</td>
<td>-0.046</td>
<td>0.939</td>
<td>-0.305</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.024</td>
<td>-0.047</td>
<td>0.936</td>
<td>-0.317</td>
</tr>
<tr>
<td>IRA</td>
<td>Measured</td>
<td>-0.020</td>
<td>-0.042</td>
<td>0.944</td>
<td>-0.299</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.022</td>
<td>-0.043</td>
<td>0.939</td>
<td>-0.312</td>
</tr>
<tr>
<td>EGW</td>
<td>Measured</td>
<td>-0.040</td>
<td>-0.069</td>
<td>0.905</td>
<td>-0.340</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.041</td>
<td>-0.073</td>
<td>0.903</td>
<td>-0.345</td>
</tr>
<tr>
<td>SW</td>
<td>Measured</td>
<td>-0.036</td>
<td>-0.030</td>
<td>0.923</td>
<td>-0.306</td>
</tr>
<tr>
<td></td>
<td>Modeled (with reconstructed $\varepsilon$)</td>
<td>-0.033</td>
<td>-0.028</td>
<td>0.924</td>
<td>-0.306</td>
</tr>
</tbody>
</table>

#### Analysis of Measurement Data

The established quality of permittivity reconstruction is achieved particularly due to the excellent data generalization demonstrated by the RBF network. We attribute these principally amended generalization capabilities to the following factors:

1. using the inverse type of the ANN,
2. regularizing the problem with ridge regression [Orr, 1996] aiming to improve smoothness of data in the DBs, and
3. optimizing the RBF’s radii (when the local Gaussian RBF is used).

These functions contribute to the improved learning and interpolating abilities of the network and allow us to deal, without any special pre-processing, with real experimental (noise-contaminated) data.

Here we illustrate the network operations by some details in reconstructing the $\varepsilon'$ and $\varepsilon''$ of DA and SW. The $\varepsilon$-plane’s sub-domains of the secondary DBs (Figures 7(a) and 7(d)) mapped to the $S_{11}$- and $S_{21}$-planes are visualized as the curvilinear regions shown in Figures 9 and 10. Imperfection of the experimental data can be seen from the fact that when the complex
values of measured reflection and transmission coefficients are plotted in these $S_{11}$- and $S_{21}$-planes, they fall into different sub-domains – for instance, VII and IX in case of DA (Figure 9). The ANN procedure fed by these experimental data finds that the reconstructed point ($\epsilon'$, $\epsilon''$) is located in sub-domain VIII; this point mapped into the $S_{11}$- and $S_{21}$-planes is also plotted in the graphs of Figure 9. In order to perform this reconstruction, the exploited inverse RBF network does not require the values of measured $S$-parameters to appear strictly within the 12 domains of the $S_{11}$- and $S_{21}$-plane (which would be the case with the direct network) and thus allows for a greater dispersion in experimental data which may not necessarily fall into the ranges conditioned by the boundaries of the secondary DB. An occasional location of the measured complex $S_{11}$ outside these domains is exemplified by the case shown in Figure 10(a). This important advantage favorably distinguishes our approach from the ones based...
on the direct networks [Olmi et al., 2002; Eves et al., 2004a] and makes the entire technique particularly flexible and efficient.

It is worth noting, however, that uniqueness of values of $\varepsilon'$ and $\varepsilon''$ reconstructed from the complex reflection and transmission coefficients has been proven so far only for a parallel-plane waveguide (a 2D case) [Shestopalov and Yakovlev, 2007], and while uniqueness is expected to be held for a general waveguide (a 3D problem), it remains an assumption in our reconstruction method. Related complications in practical use of the present method may be associated with several solutions numerically close to each other: we observed situations when training the network by sparse primary DBs had resulted in ambiguous indications regarding the $\varepsilon$-plane’s zone supposedly containing the solution. It has been found that this issue can be normally overcome by repeated training with the use of a denser DB – provided that these close multiple solutions are not caused by noisy experimental data. A radical resolution of the latter difficulty would require some additional mechanisms – such as filtering noise from experimental data or training the network by data with additive noise [Wang and Principe, 1999]. This may become a subject of further development of the method.

CONCLUSION

It has been demonstrated that the presented neural-network-based FDTD-backed technique of complex permittivity reconstruction is capable of efficiently determining the dielectric constant and the loss factor of diverse materials placed in a waveguide-type cavity. While the computational part of the method is shown to be very accurate, the experimental part is reduced to measuring complex reflection and transmission coefficients of the fixture. Due to the association with a universal numerical technique (the 3D conformal FDTD method) which is highly versatile in terms of geometry of considered scenarios, the method has the potential to be independent of the shape of the cavity or the sample. The technique is expected to be applicable to any 3D objects that could be constructed in the models of the accompanying FDTD solver (in our case, QuickWave-3D) whose simulations are controlled by our neural network algorithm. It has been shown that the accuracy of reconstruction may depend on a practical implementation of the method; for the considered WR975-based fixture containing relatively small samples, the technique may experience difficulties in highly precise determination of low-valued complex permittivity.

Because of the employed two-port approach, the method is also frequency-independent and allows for handling of dispersive materials. For materials which can take some predefined form, the computational cost of the method is very insignificant; with pre-computed DBs, it could be used in real-time measurement of $\varepsilon'$ and $\varepsilon''$. To make the method self-sufficient in terms of validation of the results and to keep its performance under control, a convenient modeling-based validation technique has been introduced and used in reconstruction of the dielectric constant and the loss factor for 6 sample liquids (including acetone and three types of alcohol) whose dielectric properties at 915 MHz have never been determined. The improved learning and interpolating abilities of the network working with noise-contaminated experimental data have also been demonstrated.

Due to all of its favorable qualities, our method has proved to be an efficient practical technique of complex permittivity reconstruction well suited for routine use in an industrial environment. Further development of the method may be two-fold and focused on (1) design of alternative/modified two-port fixtures dedicated to the samples of special geometries and/or the materials with low $\varepsilon'$ and $\varepsilon''$ and (2) the extended capabilities of the network in processing practical noisy experimental data.
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