Neural Networks for Microwave Characterization of Arbitrary Shaped Material Samples in Leaky Cavities

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Abstract — In this paper, we present simulations of a microwave sensor in a cylindrical leaky metallic cavity partially filled with arbitrary shaped material samples. Each resonant modes where excited by a funnel shaped monopole inside the front door of the cavity. A preprocessing stage was used to generate a proper database of characteristic values from the magnitude of the scattering parameter $|S_{11}|$ of the received signal only, since the phase information is not available for low cost applications. Subsequently, by using a multilayer perceptron (MLP) network, the dielectric constant, the dielectric losses and the amount of the unknown material can be accurately extracted from these characteristic values. Detailed investigations to the input values where done to understand the complexity of the problem. MLP-networks with different numbers of inner neurons where trained using only less than half of the generated database for test and validation. Accurate results for the detection of the dielectric constant and the losses of the material where obtained whereas the detection of the material size is relatively poor.

I. INTRODUCTION

In microwave technology, a cavity completely loaded with unknown dielectric lossy material is widely used to characterize it, e.g. to extract its dielectric constant and its losses. However, it is difficult to characterize a material sample, if it is not possible to fill the whole cavity with unknown material or at least, to use a sample with well defined dimensions. The problem becomes even worse, if only the magnitude of the scattering parameter $|S_{11}|$ is known, since the phase of $S_{11}$ is often not available from microwave measurements in low cost applications. Nevertheless, to extract the dielectric constant, its losses and the amount of the material samples, we already introduced a novel neural network model, which only requires the magnitude of $|S_{11}|$ in a previously defined frequency range. So far, this method works very well for material samples with low losses as already shown in [1]. The reverse case, to extract the resonance frequency in dependence of the dimensions and the properties of a load using neural networks can be found in [2]. In this paper simulations where done in order to characterize material samples with unknown dielectric constant $\varepsilon_r$, losses $\tan \delta$ and amount of material in a model of a real leaky cavity. The model was replicated as true to the original cavity, so that several fixtures in the real cavity and also hollows in the door where added to a simple model of the cavity. Simulations to this problem where done using the commercial FITD based simulation tool CST-Microwave Studio. The model was implemented into the simulation tool and two databases consisting of altogether 150 datasets where generated.

Multilayer perception networks with different numbers of neurons where trained only by using the characteristic parameters from $|S_{11}|$ to extract these unknown parameters.

To compare two trained neural networks a figure of merit was defined for each neural network, which is given by the percentage of misclassified datasets. A dataset is misclassified if either the material parameters ($\varepsilon_r, \tan \delta$) or the amount of material differ more than one parameter step.

II. NEURAL NETWORKS

Today, neural networks represent a good alternative to classical approaches solving problems without any analytical solution. Several types of architectures of neural networks for different applications can be found in [3].

The connection between material properties as well as the amount of material and the corresponding resonance spectrum can be approximated by linear continuous functions, when the dielectric and magnetic properties of the materials in the cavity differ only slightly. When there is a big difference between the material properties as it is in this case, the functions are no longer linear. Nevertheless, the assumption of a continuous behavior of the parameters is still a good approximation.

Multilayer feed forward networks are an appropriate choice to approximate these functions. This is stated by the universal approximation theorem which proves that any continuous function can be approximated by a suitable three layer feed forward network (input-, hidden-, and the output-layer) [4].

The architecture of the neural network model is shown in Fig. 1. The input parameter vector $R$ is weighted by the input weights $IW^{1:1}$ and added to the bias vector $b^1$. A set of sigmoid activation functions is required to determine the activation states of each neuron in the first layer. The
second layer is identical to the first layer except the activation functions. To get output parameters with large linear ranges the activation functions in the last layer have to be linear. The investigated neural networks are trained by the Bayesian method, which is extreme efficient for such problems [5].

Because of the size and the redundancy of the frequency samples measuring $|S_{11}|$, it is not possible to use all samples as input parameters for the neural network, in fact a preprocessing stage is necessary to extract characteristics of the spectrum (resonance modes, radiated power etc.). For these analyses a mode tracking process was chosen to extract resonance modes from the spectrum.

### III. Experimental Approach of a Leaky Cylindrical Cavity

For the applications in mind, a leaky cylindrical cavity is given to detect the dielectric properties of materials in the microwave region. For further processes within the cavity often it is necessary to know the complex dielectric properties ($\varepsilon_r$ and $\tan \delta$) as well as the amount of material. If the cavity is completely filled with the unknown material, the parameters can be obtained by the use of analytic equations extracting complex resonant frequencies of different modes of the cavity. If the cavity is only partly filled with material an analytical solution is no longer possible.

In Fig. 2 a model of a leaky cylindrical cavity is shown. The cavity is partly opened on the left side and there are several fixtures in the cavity. A funnel shaped monopole is used to insert the microwave signal into and out of the cavity. The cavity itself is partly filled with material and air. The neural network model is used to extract the complex dielectric properties as well as the amount of material in the cavity. The position of the monopole is chosen so that $TM_{01n}$ modes can exist.

If the cavity is empty, the field distribution is symmetrical (shown in Fig. 3, on the upper left picture). If dielectric material with low conductivity is inserted into the cavity, the field distribution changes. At the transition from air to material, the direction of the field vectors are changed according to the law of refractions for dielectric materials at microwaves. The field distribution is shown in the upper right part of Fig. 3. If the conductivity is increased, the fields within the material vanishes. The corresponding field is shown in the lower left part of Fig. 3. If the losses within the material are low then also resonances within the material can exist according to the lower right part of Fig. 3.

The corresponding reflection parameter $|S_{11}|$ of the partially filled cavity in dependency of the losses and the filling factor is shown in Fig. 4. If the losses of the material increase, the resonances vanish and the extraction with the neural network system is no longer possible.

To find neural networks that are able to extract the complex permittivity of the material in the cavity as well as its amount, frequencies below 1 GHz where investigated. Four resonant modes ($TM_{011}$, $TM_{012}$, $TM_{013}$ and the $TM_{014}$ mode) can exist in this frequency range. Only the $TM_{011}$ and $TM_{012}$ modes are used to generate the training and test databases, because these modes are still available for high fillings and moderate losses.

A preprocessing stage extracts the resonant frequency, the corresponding value of $|S_{11}|$ and a value $K$ which is inversely proportional to the quality factor of the cavity for both modes in the database. The low quality factor of the cavity itself and moderate losses due to the material in the cavity can lead to ambiguous values of the Q-factor. Therefore the maximum
value of the autocorrelation function of the band pass filtered signal is chosen as a characteristic value due to the inverse of the Q-factor. The database is divided into two parts, one to train and one to test the neural networks.

The extraction of the complex scattering parameter $S_{11}$ would increase the accuracy of such a system, but is accompanied with significantly higher costs. However, the practical constraints to design a sensor system for low cost and to accept a moderate accuracy leads to skip the phase information.

Fig. 5 to 7 show the behavior of the parameters extracted from the $TM_{011}$ mode. In Fig. 5, the resonance frequency of the $TM_{011}$ mode versus the relative permittivity and the filling factor of the cavity is shown. As one can see, the resonance frequency is proportional to the permittivity and to the filling factor of the cavity. A change in the losses of material in the cavity causes a decrease of the resonance frequency as shown by the different parameter planes in the figure.

Fig. 6 shows the behavior of the absolute value of $S_{11}$ versus permittivity and filling factor. The filling factor is the volumetric percentage of the cavity volume. If the filling factor or the permittivity rises the absolute value of $S_{11}$ first decreases and then rises up again and therefore causes to ambiguous values when the losses rise.

The K-factor of the $TM_{011}$ mode behaves in the same way then the resonance frequency. In Fig. 7 this behavior is shown. Rising up the losses of the material in the cavity causes to lower changes of the K-factor. The second resonance frequency investigated is the $TM_{012}$ mode. In principle, figures 8 to 10 show the same behavior than for the $TM_{011}$ mode except for higher filling factors and higher dielectric constants.

Fig. 8 exhibits the resonance frequency of the $TM_{012}$ mode dependent on the permittivity and the losses. This figure shows that the behavior due to the losses is no longer unambiguous. The behavior of the absolute value of $S_{11}$, shown in Fig. 9, is similar to the one of the $TM_{011}$ mode.

Fig. 9. $|S_{11}|$ as a function of permittivity and losses for the $E_{012}$ mode
Two databases were created to train and test the neural networks.

Database 1 consists of
- filling factors from 5% up to 30% in 5% steps,
- losses from $\tan \delta = 0.002$ up to $\tan \delta = 0.01$ in steps of 0.004 and
- relative permittivities from $\epsilon_R = 1.1$ to $\epsilon_R = 1.5$ in steps of 0.2.

Database 2 consists of
- filling factors from 5% up to 30% in 5% steps,
- losses from $\tan \delta = 0.004$ up to $\tan \delta = 0.008$ in steps of 0.004 and
- relative permittivity from $\epsilon_R = 1.2$ to $\epsilon_R = 1.4$ in steps of 0.2.

IV. RESULTS

In the upper part of Fig. 11 the classification errors for different trained neural networks are shown. Here a misclassification occurs, when one or more of the detected material samples are misdetected. That means, if the detected filling factor differs more than 2.5% of the cavity height or the detected losses differ more than 0.002 or the relative permittivity differs more than 0.1 from the real simulated parameters. The upper part of Fig. 11 shows that a well trained neural network is able to detect more than 75% parameter sets of the test database. A neural network with only 21 neurons (11 neurons in the first layer and 10 neurons in the second layer) is sufficient. The upper part of Fig. 11 shows the classification errors due to the different neural networks whereas the lower part shows the absolute errors detected by the neural Network 11.10. If the threshold of the classifier is doubled for all three values, which means that the network is not able to differentiate between two adjacent parameter sets, but between two the parameter sets next to the adjacent ones, the neural network is able to detect more than 90% of the test database correctly.

V. CONCLUSION AND OUTLOOK

A novel model has been developed only from the simulated magnitude of the scattering parameter $|S_{11}|$ with the aid of a neural network to extract the material parameters and the filling factor of partially filled loads in a cavity at microwaves. The simulations show that it is possible to extract properties of lossy dielectric materials using well trained neural networks.

The results showed that a well trained neural network is able to detect more than 75% parameter sets with high accuracy and more than 90% of the test database for a moderate accuracy. The experimental verification of the material parameter extraction from cylindrical leaky cavities are of interest for a certain industrial application and will be considered in near future.

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