Neurocomputed Model of Open-Circuited Coaxial Probes

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Abstract—**An artificial multi-layered feedforward neural network has been developed which transforms reflection coefficient data measured using a coaxial probe and network analyser, into the permittivity values of the fluid the probe touches. This eliminates the need for de-embedding of data from the measurement plane via empirical models of the physical cable. Back propagation training and testing was performed on a 0.25 in. diameter coaxial probe, using data spanning the frequency range 200 MHz–16 GHz taken on nine fluids. The successful results indicate that a new nonparametric technique can join the other permittivity measurement schemes for coaxial probes.**

I. Introduction

There have been many attempts to accurately measure the permittivity of substances using a noninvasive coaxial probe that rely on modeling the admittance at the tip of the probe [1]–[3]. Each method requires some knowledge of the physical structure of the probe tip in order to de-embed from the measurement plane of the network analyser to the sensor plane where the probe touches the fluid (Fig. 1). Our application of an artificial neural network technique circumvents any parametric model of the cable. Instead the trained neural network receives a vector of measured reflection coefficient data and directly outputs the permittivities that correspond to the substance under investigation.

II. De-Embedding

Previous de-embedding methods have been based upon the Stuchly [1] and Misra [2] models for calculating permittivity. The admittance model for the tip of the coaxial probe plays a crucial part in the transformation of the measured reflection coefficient $\rho(i, f)$ at the sensor plane to the reflection coefficient at the tip of the probe $\rho\_tip(i, f)$ via (1) below

$$\rho\_tip(i, f) = \frac{\rho(i, f) - Ed(f)}{Es(f) \cdot [\rho(i, f) - Ed(f)] + Er(f)}. \quad (1)$$

The vectors Es, Er, and Ed, the so-called error coefficients, are calculated prior to de-embedding. They depend on measured reflection coefficients $\rho(i, f)$ and the known permittivity values for three fluids selected as standards. One form of

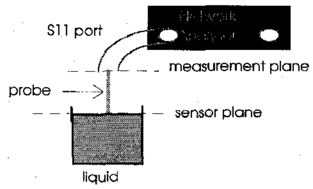

Fig. 1. Experimental setup for measuring reflection coefficients of liquids.

the Misra admittance of an open-ended coaxial probe [2] at microwave frequencies is

$$Yt(f, \varepsilon) = j \cdot \frac{2 \cdot \omega(f) \cdot I1}{\left(\ln\left[\frac{b}{a}\right]\right)^2} \cdot \varepsilon \cdot \varepsilon o - \left[j \cdot \frac{[\omega(f)]^3 \cdot \mu \cdot I2}{\left(\ln\left[\frac{b}{a}\right]\right)^2} \cdot (\varepsilon \cdot \varepsilon o)^2 \right] + \frac{\pi \cdot \omega(f)^4 \cdot \mu^{3/2}}{12.} \cdot \left[\frac{b^2 - a^2}{\ln\left[\frac{b}{a}\right]} \right]^2 \cdot (\varepsilon \cdot \varepsilon o)^{5/2} \quad (2)$$

where a and b are inner and outer radii of the 0.25-in. (6.4 mm) Teflon probe—$a = 0.814 \cdot 10^{-3}$ m, $b = 2.6545 \cdot 10^{-3}$ m; $I1$ and $I2$ are integrals given as $I1 = 3.092 \cdot 10^{-3}$ m and $I2 = -6.930 \cdot 10^{-9}$ m^3; and $k(f)$ is the wave number. Having calculated $\rho\_tip(i, f)$ via the *Misra* admittance model, the unknown permittivity at a specified frequency is found by solving (3) for complex permittivity, ε.

$$\frac{1 - \rho\_tip(f)}{(1 + \rho\_tip(f) \cdot Zo)} = Yt(f, \varepsilon) \quad (3)$$

Misra's empirical model is only an approximation and does not incorporate second order effects such as temperature effects [5]. Permittivities obtained after de-embedding with any specific three standards are often quite different from those determined by de-embedding with three other standards.

III. Applying the Neurocomputing Technique

The choice of the size, type of architecture, and the form of the transfer functions of an artificial neural network is dependent on the input data and the problem to be solved [6].

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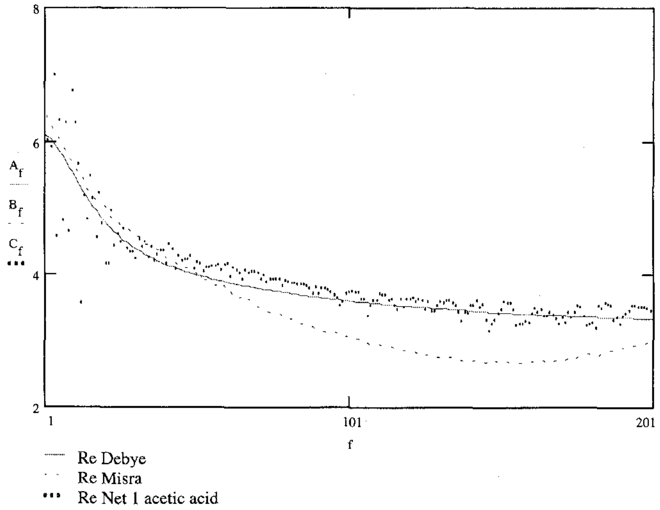

Fig. 2. Comparison of real parts of permittivity for acetic acid.

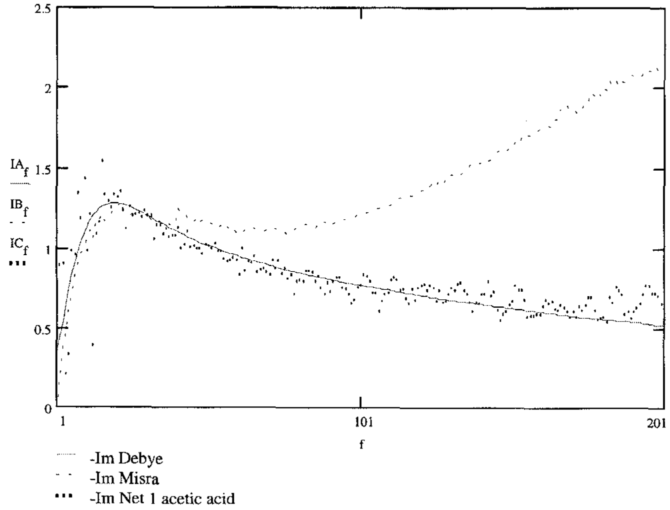

Fig. 3. Comparison of imaginary parts of permittivity for acetic acid.

For our work, a multi-layered feedforward (MLF) network [7], [8] was chosen and trained by adjusting the interconnection weight coefficients using back propagation [6], [7], [9], [10]. The MLF network consists of an input and output layer of processors and two intermediate (hidden) layers of processors. This choice is slow at converging, however the MLF network is capable of determining reliable and robust solutions, and complex inter-relationships in the data by performing some degree of interpolation and extrapolation [12], [13].

Two two-layer network architectures were finally selected as near optimal. Network One used a first hidden layer of 8 processors with a second hidden layer of 12 processors, while Network Two used 8 and 20 processors, respectively. Back-propagation training reduces the difference between the actual output and the desired result (output error) by iterative adjustment of the interconnection weights. The output error is reduced until both the error and its time derivative are close to zero for the complete training data set.

Our data sets comprised a matrix of 201 frequency dependent vectors having eleven input values and two output values for each of the nine fluids studied. Five of the inputs consisted of the real part of the reflection coefficient expanded via the Chebyshev series [11] to fifth order; five of the similarly expanded imaginary part and one further input of frequency. The two outputs are the desired scaled real and imaginary training permittivity values. The Chebyshev expansion [14] is given by the general formula:

$$T_n(x) = \cos(n \cdot \arccos(x)) \tag{4}$$

where $1 < x < 1$ is the real or imaginary part of the measured reflection coefficient, and $n = 1, 2, \cdots, 5$. Network One used a training mode where weights were updated with each new example presented. Network Two used a different training mode in which 67 randomly chosen frequencies for each fluid were used in each training batch of 603 examples before each weight change was made. The correctness of the solutions were confirmed by testing the neural network with an independent data set with a known outcome. Once a suitable solution was determined, the weights were then fixed and new data presented to the network in the feedforward manner only to allow unknown permittivity measurements.

TABLE I
COMPARISON OF ROOT MEAN SQUARED ERRORS IN CALCULATION OF PERMITTIVITY FOR NINE FLUIDS COMPARED TO THE RESULTS FROM DEBYE EQUATION

Fluids\ Model	Misra	Network 1	Network 2
Acetic Acid	0.931	0.318	0.529
Butanol	0.896	0.309	0.315
Chlorobenzene	1.116	0.669	1.048
Cyclohexane	0.444	0.404	0.705
Ethylene Glycol	0.98	0.683	1.368
Ethanol	1.072	0.887	1.23
2-methyl propanol	0.843	0.359	0.403
Pentanol	0.769	0.417	0.423
Propanol	0.959	0.438	0.526

IV. RESULTS

Testing of the network took the form of systematically applying all of the reflection coefficient data to the inputs. Typical output results after rescaling can be seen in Figs. 2 and 3, compared with the actual Debye permittivities obtained from fitting of the Debye equation to data measured in waveguide [4]. Both networks gave results which exceed the best outputs of the Misra model. The figures show real and imaginary permittivity parts of acetic acid, for 201 frequency points from 200 MHz–16 GHz. Comparisons are between Debye, Misra and the output of Network One.

V. ERROR ANALYSIS

Table I shows the root mean squared errors for permittivities obtained from each model, for each fluid compared to the Debye determined values. Clearly Network 1 is significantly better than the Misra model for all fluids and Network 2 is generally better. Standards of air, methanol and water were used in the Misra model to de-embed reflection coefficients for all other substances.

VI. Discussion

A distinct advantage of neurocomputing is that a neural network completely bypasses the parametric tip model. Our models produce permittivities which do not involve de-embedding. While the results from neural networks show more variation at low frequencies, we have seen they are always close to the correct values and significantly closer than the results from a conventional de-embedding model. Having trained a neural network on a variety of different fluids for one particular coaxial probe, reflection coefficient measurements taken by that probe are directly converted into permittivities, provided the experimental data corresponds to one of the training fluids and is within the range of training frequencies. Network 2 appears to suffer slightly from over-generalization, possibly because it uses more weights than Network 1. The uncertainties in the known permittivities of the reference fluids will influence the measured permittivities of unknown materials. A complete accuracy analysis taking this into account is the subject of further study.

VII. Conclusion

The neural network described above has demonstrated the success of neurocomputing applied to a difficult empirical problem. Our multi-layered back-propagation trained neural networks take reflection coefficient data measured by a coaxial probe and transform these measurements directly into permittivity values. Advantages of neurocomputing include: flexibility—a single architecture has produced a model for the data from nine fluids with considerably different permittivity values over a two decade frequency range; and good accuracy—more accurate output permittivities were determined when tested against a Misra tip model. Finally, the ease of implementation of neurocomputing in this field should attract future investigators to experiment with this new approach.

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