Complex-Valued DNN for Broadband Dielectric Characterization of Dispersive Lossy Materials

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***Abstract*—This paper presents a broadband dielectric characterization method based on a Complex-Valued Deep Neural Network (CVNN) that allows the retrieval of permittivity and conductivity of dispersive lossy materials using ad-hoc setups. To validate the method, we numerically tested it employing a partially filled custom-made double-ridge waveguide setup, working from 0.95 to 4.2 GHz. Moreover, we include a feature importance analysis using agnostic explainable-AI (XAI) techniques. The results demonstrate the flexibility and the retrieval capabilities of the method, as well as the advantages and drawbacks in comparison with traditional techniques. We publicly release the dataset and codes to support further research.**

***Index Terms*—Complex-valued neural networks, dielectric characterization, explainable artificial intelligence**

I. Introduction

Dielectric properties (DP), i.e., permittivity (ϵ_r) and conductivity (σ), are essential in several fields, such as electronics and electromagnetic compatibility, food and agriculture, and biomedical, where they can act as sensing parameters, degree of design freedom, and performance boosters, among other uses [1]. So, over the years, different characterization methods have been developed adapting to the diverse application requirements and material under test (MUT) features like frequency operation band, losses, dispersiveness, and the sample's form and size. For instance, the open coaxial method is ideal for characterizing liquids. It uses the measures of at least three calibration standards, e.g., open, short, and known material, to determine the MUT's DP [1]. Another example is the resonant cavity method. It determines the DP of solid and semi-solid materials employing the cavity physical model and the resonant frequency shifting occurring when the cavity is filled with a MUT sample. Thus, it is highly accurate for low-loss materials but is narrowband [1].

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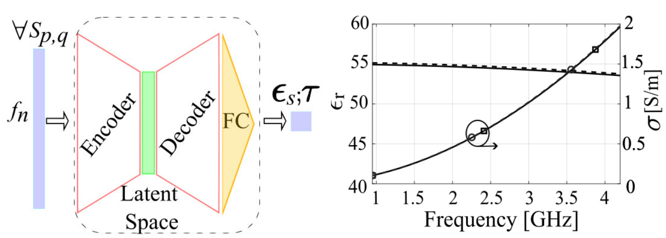
This work introduces and exploits a complex-valued deep neural network (CVNN) to determine DP. Specifically, we train and validate the method using synthetic data obtained via full-wave simulations of a custom-made double-ridge waveguide setup [2], working from 0.95 to 4.2 GHz, partially filled with a sample of lossy dispersive material that for the sake of the test takes DP values ranging those of human tissues [3]. The CVNN approach allows a broadband characterization using a single measurement and a non-trivial physical modeled configuration with a smaller sample, which is essential in many applications. The network uses as input a set of S-parameters (SP) and outputs the first order Debye parameters [4], i.e., static permittivity, ϵ_s, and the relaxation time, τ, which are used to determine ϵ_r and σ. Moreover, it is worth noticing the network is physically informed, including physical limitations such as the low influence, for the training dataset, of the infinite permittivity, ϵ_∞, of the Debye parameter at the interest frequencies [4].

II. Methodology

Since the dielectric characterization from SP is a nonlinear inverse problem that demands a rigorous mathematical formulation of the measurement fixture, deep neural networks (DNNs) are found to be effective [5]–[7] in modeling the nature of the problem due to their strengths in approximating non-linearity while reaching convergence. To this end, multi-layer perceptron (MLP) is a widely utilized DNN method which is based on the universal approximation theorem. However, despite SP being in the complex domain, i.e., $\forall \{p, q\} \in \mathbb{N} : S_{p,q} = s_{p,q,R} + is_{p,q,I} \in \mathbb{C}$, the existing works either consider (1) real and imaginary components separately ($s_{p,q,R}, s_{p,q,I}$) [5], (2) only the magnitude ($|s_{p,q,R} + is_{p,q,I}|$) [7] or (3) only the real component ($s_{p,q,R}$), and thereby inherently lack the potential to fully-harness the entire available information in complex SP. To this end, we propose a CVNN that has the ability to process complex-valued SP to predict DP. Furthermore, unlike the typical practice of heuristically-designed architectures [5], [6], we design our CVNN architecture via an automated pipeline empowered by neural architecture search (NAS). The target of NAS process is to systematically determine the number of neurons per hidden layer in the neural network while objectively experimenting with network hyperparameters. The final CVNN configuration is subsequently selected from the search space such that it has the least cost in DP prediction. As illustrated in Fig. 1a, our NAS-designed CVNN model primarily comprises an autoencoder-like architecture followed by regressing fully connected (FC) layers in the high-level overview. It accepts a 3-D tensor of scattering parameters S_{p,q,f_n} where $p, q, n \in \mathbb{N} \cap \{p, q, n | p, q \leq 2; n \leq 1001\}$, and p and q indicates the receiving and transmitting index, and f_n the frequency dimension, and outputs a 1-D vector of $\{\epsilon_s, \tau\}$. Moreover, we include a feature importance analysis employing a set of model-agnostic explainable-AI (XAI) techniques, namely (1) model ($f[.]$) weights analysis: $\frac{1}{L}|f[W[0]]|$ where $W[0]$ is the aggregated weight matrix between the input and first hidden layers while L is the linear normalization factor, and (2) permutation response where the difference between baseline error: $\zeta\{y, f[\mathbf{x}]\}$, and permuted error: $\zeta\{y, f[\mathbf{x_p}]\}$ is utilized to assess feature significance [8].

III. Experiments and Results

We use a dataset with 145 simulations which is randomly split into training and test sets with a $3:1$ ratio, respectively. Due to the regression nature of the task, we evaluate our CVNN method using five related metrics: (1) mean squared error, $MSE = \frac{1}{N}\sum_{i=1}^{N}\{y_i - \hat{y}_i\}^2$, (2) mean absolute error, $MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$, (3) mean percentage error, $MPE = \frac{100\%}{N}\sum_{i=1}^{N}\frac{1}{y_i}|y_i - \hat{y}_i|$, (4) Pearson correlation coefficient, r, and (5) Spearman's rank correlation coefficient, ρ, where y, $\hat{y}$, and N refer to ground truths, predictions, and the number of samples in the test set, which is not used in model



(a) (b)

Fig. 1: Illustration of CVNN model and its performance. (a) High-level CVNN architecture and (b) DP retrieval test.

TABLE I: DP estimation metrics*

Method	MSE↓	MAE↓	MPE (%)↓	r ↑	ρ ↑
static permittivity (ϵ_s)					
[5]	$6.87_{\pm 2.23}$	$1.61_{\pm 0.33}$	$9.30_{\pm 0.76}$	<u>0.98</u>	<u>0.97</u>
[7]	$5.45_{\pm 0.14}$	$1.34_{\pm 0.11}$	$8.87_{\pm 0.31}$	**0.99**	<u>0.97</u>
[6]	$12.64_{\pm 8.22}$	$2.48_{\pm 0.82}$	$14.25_{\pm 4.93}$	0.97	0.96
DNN-1	<u>3.81</u>$_{\pm 0.26}$	**0.89**$_{\pm 0.04}$	<u>7.35</u>$_{\pm 0.20}$	**0.99**	**0.98**
DNN-2	$4.59_{\pm 0.33}$	$1.06_{\pm 0.06}$	$8.09_{\pm 0.16}$	**0.99**	**0.98**
CVNN	**3.39**$_{\pm 0.14}$	<u>0.92</u>$_{\pm 0.04}$	**6.25**$_{\pm 0.27}$	**0.99**	**0.98**
relaxation time (τ)					
[5]	$3.00_{\pm 2.79}$	$1.05_{\pm 0.55}$	$32.02_{\pm 56.18}$	0.87	0.85
[7]	$0.95_{\pm 0.10}$	$0.63_{\pm 0.04}$	$27.48_{\pm 2.49}$	<u>0.96</u>	<u>0.95</u>
[6]	$5.29_{\pm 3.70}$	$1.64_{\pm 0.80}$	$44.30_{\pm 75.93}$	0.76	0.75
DNN-1	<u>0.87</u>$_{\pm 0.02}$	<u>0.54</u>$_{\pm 0.02}$	<u>15.94</u>$_{\pm 2.25}$	**0.97**	<u>0.95</u>
DNN-2	$0.99_{\pm 0.03}$	$0.60_{\pm 0.02}$	$17.77_{\pm 4.52}$	<u>0.96</u>	<u>0.95</u>
CVNN	**0.81**$_{\pm 0.01}$	**0.52**$_{\pm 0.02}$	**14.59**$_{\pm 0.58}$	**0.97**	**0.96**

*Metric-wise, best performance is made bold while second best is underlined.

training, respectively. Exact details of the hyperparameters for the proposed method are reported in the repository[1].

As presented in Table I, our CVNN method consistently and significantly outperformed the existing works across all metrics, validating the superiority of the designed DNN architecture through NAS. Further, it is observable that even with the same architecture, having SP as complex numbers gives an edge in performance over transforming them to real representations, as shown against DNN-1 ($s_{p,q,R}, s_{p,q,I}$) and DNN-2 ($|s_{p,q,R} + is_{p,q,I}|$). Figure 1b exemplifies the DP retrieval of cerebrospinal fluid [3] which was not included in the training data. In addition, we also employed XAI techniques to validate the physical consistency of the model's predictions, using network with optimized hyperparameters.

IV. Conclusion

This study introduced and validated a broadband method for the dielectric characterization of dispersive and lossy materials using a complex-valued neural network, outperforming traditional methods in accuracy and prediction capabilities.

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